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THESIS

AN ANALYSIS PLAN FOR THE ARCOMS II EXPERIMENT

by

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The purpose of this thesis is to examine and recommend methodologies that will support the analysis of the ARCOMS II field experiment. This is done in three parts. The first is to determine the methods with which to analyze the experimental effects and interactions. This is followed by a discussion of data analysis techniques for representing the

data. Thirdly, an examination of the techniques for determining the significance of certain questions relating to the Armor Combat Process is discussed.

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An Analysis Plan for the ARCOMS II Experiment

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ABSTRACT

The purpose of this thesis is to examine and recommend methodologies that will support the analysis of the ARCOMS II field experiment. This is done in three parts. The first is to determine the methods with which to analyze the experimental effects and interactions. This is followed by a discussion of data analysis techniques for representing the data. Thirdly, an examination of the techniques for determining the significance of certain questions relating to the Armor Combat Process is discussed.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

I. INTRODUCTION

A. BACKGROUND

Decision-making within the Armed Forces has evolved into an extremely complex process requiring an ever increasing dependence upon quantitative tools such as combat modeling and computer simulation. In view of this situation the Defense Department recognized the importance of the data required as input to these models. Consequently, the Army has undertaken a program of models improvement supported by field experimentation. In response to this effort the Training and Doctrine Command (TRADOC) designated the TRADOC Systems Analysis Activity (TRASANA) as the proponent for a series of field experiments to provide the Army Model Improvement Program the required support. Furthermore, It directed the Tradoc Combined Arms Test Activity (TCATA) at Fort Hood, Texas to conduct the first of these experiments. This initial experimentation was quickly followed by the Armor Combat Operations Model Support (ARCOMS) Field Experiment Phase II (ARCOMS II). The ARCOMS II force-on-force engagement experiment was designed to provide data that would enable modelers to better understand the direct fire combat processes in both offensive and defensive operations; the result of which is the eventual improvement in Armor combat modeling, combined arms simulation and wargamming. Among the critical issues to be addressed were the time and range dependent distributions of the "dependent variables" during the force-on-force engagements as well as the experimental effects and interactions [Ref. 1: pp. 1-1 thru 1-10].

1. Scenario

The scenario for this experiment consisted of a series of combined arms meeting engagements between ATTACKER and DEFENDER forces configured as shown in Table I [Ref. 1: p. 1-5], The force configuration depicted here is typical of an Armor heavy team attacking an Armor platoon supported by anti-tank weapons. The specific quantities of each force element were allocated in order to provide the Attacker with the minimum force ratio of three to one.

TABLE I
FORCE COMPOSITION

EQUIPMENT TYPE	OFFENSE BOUNDING	OFFENSE OVERWATCH	DEFENSE
Tank, M60	2 platoons	1 platoon	1 platoon
APC	1 platoon		
AT		1 section	1 element

The scenario was designed to play US and OPFOR tactics in both offensive and defensive operations. The opposing forces were given initial briefings and operations orders. The test officers acted as both the controllers and the higher headquarters for the participating units. The players were permitted to conduct the operation to the best of their experience and ability so long as they remained consistant with the tactical doctrine that they were selected to represent. The attacking force commenced

deployment from one of two selected avenues of approach. Their objective was to seize positions being defended by the opposing force. From this point the meeting engagement was free flowing. This permitted the tactical play to be as realistic as possible. Artillery, smoke, mines and the use of trenches were not played.

2. Data Collection

Prior to the conduct of the experiment data on the following environmental areas was collected.

1. Meteorological data.
2. Player demographics.
3. Equipment demographics.
4. Historical questionaires.

This was followed, a short time later, by the experimental phase in which the employment of automated measuring and recording devices enabled data collection to be performed in "real time". Additionally, this method of data collection provided a means to amass an enormous quantity of data pertaining to position location, firer and target identification, range, and a record of hits and misses, just to name a few. The data collected on the dependent variables consisted of five types. They are

1. Line-of-sight data(intervisibility).
2. Target aquisition data.
3. Target distribution data.
4. Target engagement results.
5. Attrition data.

3. Dependent Variables

The dependent variables that were measured [Ref. 1: pp. 1-20 thru 1-33] are too numerous to be listed here. They are, however, provided in appendix A.

4. Independent Variables

Four independent variables were chosen at which to measure the dependent or response variables. Each of these variables consisted of two levels as shown in Table II. By fixing each of the distinct combinations of the independent variable levels, an experimental trial was determined. The entire experiment consisted of eight trials each replicated a total of three times.

TABLE II
FACTOR LEVELS

INDEPENDENT VARIABLES	LEVELS
ATTACKER TACTICS	-Fire and Movement -Rapid Approach
DEFENDER TACTICS	-Deliberate Defense -Hasty Defense
TERRAIN (avenue of approach)	-Hilly (Avenue 'A') -Flat (Avenue 'B')
HATCH POSITION (visibility)	-Open -Closed

B. OBJECTIVE

It is the objective of this paper to examine those methodologies that will best support the data analysis effort following the completion of data reduction. This is to be accomplished in three parts. The first is an examination of the experimental effects. The second is to discuss data analysis techniques to describe the data. This is followed by discussion of the analysis techniques that will help to determine the significance of certain questions relating to the Armor Combat Process.

C. SCOPE

The scope of this paper will be limited to specifically addressing the questions of "What should be analyzed?" as well as "What method should be employed to perform the analysis?". In the preceding paragraph it was stated that a primary concern of experimental analysis is to determine the effect that the independent variables have upon the dependent variables. It is equally important to examine the effect that the interactions between these variables have upon the dependent variable. This is to be accomplished in the following manner.

1. An examination of current procedures in analysis of variance and factorial design analysis will be made to decide upon the best method with which to estimate the experimental effects.
2. Once an appropriate method has been selected, a procedural example will be used to illustrate the analytical process involved in the derivation and interpretation of the experimental effects.

In order to facilitate Armor Combat Modeling, the data analysis should focus upon the methods which transform the data into descriptive or predictive models. The models

include regression models as well as many well known probabilistic or stochastic models. Procedural methods will be discussed in order to obtain answers to specific questions regarding the combat process reflected by this experiment. Included in this discussion are proposals for conducting comparative analyses between these results and historical experience as well as other experimentation.

II. ANALYSIS OF EXPERIMENTAL EFFECTS

A. BACKGROUD DISCUSSION

The four independent variables each at two levels form a total of sixteen unique combinations. By measuring the dependent variable for each of these combinations it is possible to conduct an analysis of variance using a 2^4 factorial design. The independent variables will, henceforth, be referred to as the experimental factors. The factors listed in Tables II and III have been coded A through D while their appropriate levels have been designated as plus(+) or minus(-). For clarity and simplicity this coding will be used throughout the thesis when referring to a particular factor, or factor-level combination. The ARCOMS II experiment was performed by using only eight of the sixteen treatment combinations. This was due primarily to the prohibitive cost of resources [Ref. 2: p. 2-3]. Yet, each combination was replicated three times. A look at Table IV will show the combinations that were actually employed. If all possible combinations of the control variables had been utilized the 2^4 factorial design would have proven to be an efficient method by which to estimate the main effects, and the interaction effects as well as an estimate of experimental error. The main effects are the contributions that the factors Attacker Tactics, Defender Tactics , Terrain and Hatch Position have upon the experimental yield (the dependent variables). The interactions, on the other hand, consist of the simultaneous effect of a combination of two, three or four factors upon the yield. This is valid so long as the factorial model assumptions are valid.

TABLE III

EXPERIMENTAL DESIGN MATRIX

CONTROL VARIABLE	LEVELS	CODE	SIGN
Attacker Tactics	Fire and Movement	A	+
	Rapid Approch	A	-
Defender tactics	Deliberate	B	+
	Hasty	B	-
Terrain (avenue of approach)	Hilly	C	+
	flat	C	-
Hatch Position	Open	D	+
	Closed	D	-

TABLE IV

CODED EXPERIMENTAL DESIGN MATRIX

TRIAL	A	B	C	D	NO. OF REPS
1	+	+	+	+	3
2	-	+	+	+	3
3	+	+	-	+	3
4	+	-	+	+	3
5	+	+	+	-	3
6	-	-	+	+	3
7	-	+	-	+	3
8	-	+	+	-	3
No. of (+) No. of (-)	4 4	6 2	6 2	6 2	

B. ANALYSIS OF THE EVENT MATRIX

Given the event matrix in Table IV the question is then "How should it be analyzed in order to determine experimental effects?" Having already excluded the 2^4 factorial design because of the reduced number of trials, the feasibility of using other known types of factorial designs will be examined. This will involve a look at fractional factorials, and confounding of the interactions to produce sub-models of a 2^4 factorial design. Although the use of blocking variables was considered, it will not be included in this paper. This is primarily due to the fact that there does not exist a physical variable from which blocks could be generated. The introduction of a dummy blocking variable would only serve to compound the analysis of the confounding that would normally occur due to blocking.

1. A 2^{4-1} Half Fractional Factorial

Often there exists in a factorial design a certain amount of redundancy with respect to the interactions or main effects. This reduncency may be attributed to either the negligible effect of a higher order interaction or the negligible effect of a particular factor. The latter is especially true when a large number of factors are used in the design [Ref. 3: pp. 374-375]. Capitalizing upon this notion one may find it possible to reduce the number of trials and still obtain valid results. However, the little bit of freedom that is gained when an interaction or a factor is assumed to be negligible has a cost attached to it. That cost is in terms of a loss of information regarding the effect of the omitted interaction. If from experience or some prior information one knows of such a negligible effect, there will be little or no loss of information. On the other hand, if no *a priori* knowledge exists, a loss of

information that is normally attributed to the effect is likely to occur. Rather than regarding this as a loss of information, it would be more appropriate to say that the information has been confounded with some other effect. Thus an effect normally attributed to the omitted factor combination is now confounded with some other factor combination. The two effects are now indistinguishable from one-another.

Reduction in the requisite number of trials may also be accomplished by considering a half-replicate of a 2^4 factorial. A half-replicate of the 2^4 factorial is merely a 2^{4-1} or 2^3 factorial. This requires only eight or half of the original sixteen trials. Thus, it only remains to determine those eight combinations that produce the best results. The proper choice comes from confounding a higher order interaction with other factor combinations. This procedure generates two complimentary sets of eight combinations called a fold-over. Either set is equally useful for the purposes of analysis provided that measurements are taken using the selected half-replicate.

Clearly, it is important to obtain as much information as possible with regard to the main effects. To do this it is necessary to generate fold-over sets by confounding higher order interactions. This precludes any ambiguity with respect to the main effects. The fold-over sets using interactions AB, AC, AD, BC, BD, and CD were generated and an attempt was made to match the resulting treatment combinations to the eight actually used in the experiment (Table IV). Unfortunately, none of the fold-over sets produced a match. An attempt with each of the third order interactions ABC, ABD, ACD, BCD, and ABCD was also fruitless.

It became readily apparent that the imbalance in the occurrence of factors at the upper and lower level was to have an over-riding effect in using any subset of a 2^4

factorial design (see Table IV). The only sub-model that could produce the proper treatment combinations for analysis is the 2^2 factorial design or the 2x2 ANOVA. This design will, however, severely reduce the amount of useful information about the factors and interaction effects that would have otherwise been available.

2. 2x2 ANOVA With Replications

The imbalance in the treatment combinations selected for the experiment does not allow for the examination of all the 2x2 sub-models that are possible. The only possible combinations are indicated in Table V. Choosing any two of the four independent variables as factors will require that the other two be held at a fixed level. Once this is done it will be possible to examine the effects of the chosen factors.

By way of an example, if Attacker Tactics is considered to be the first factor and Defender tactics as the second, the 2x2 design for factors "A AND B" shown in Table V may be derived. Notice that this configuration requires at least four trials of the proper plus-minus combination. Since factors B, C, and D never occur together at the lower level, it will not be possible to construct an analysis of variance table using factors B and C, or B and D, or C and D.

TABLE V

THE POSSIBLE 2x2 ANOVA SUB-MODELS

"A AND B"

	A+B+C+D+	A+B-C+D+
A+	Trial 1	Trial 4
A-	Trial 2	Trial 6

"A AND D"

	A+B+C+D+	A+B+C-D+
A+	Trial 1	Trial 3
A-	Trial 2	Trial 7

" A AND D"

	A+B+C+D+	A+B+C+D-
A+	Trial 1	Trial 5
A-	Trial 2	Trial 8

The model for a 2x2 analysis of variance with replications is relatively [Ref. 4: pp. 568-570] simple. Assuming that an obsevation of the response variable is a function of the following effects

η -the grand mean.

β_i -the row effect where i=1,2

γ_j -the column effect where j=1,2

ψ_{ij} -the interaction effect

ε_{ijk} -experimental error for the observation at the kth replication where k=1,2,3

the model representing the kth observation in the ijth cell may then be written

$$Y_{ijk} = \eta + \beta_i + \gamma_j + \psi_{ij} + \varepsilon_{ijk} \tag{2.2}$$

The error terms in the model are assumed to be normally distributed with mean zero and variance σ^2.

The fictitious data in Table VI will serve to illustrate the analysis of variance procedure. Suppose it is of interest to determine the effects of factors Attacker Tactics, and Defender Tactics upon the mean time for the Defender to detect an attacker. The data in each cell represents the mean time for the defender to detect an attacker for each of the three replications corresponding to the treatment combinations in Table V. An analysis of variance table for this model as well as a solution using the Biomed computer subroutine, BMDP2V, is provided in Appendix C [Ref. 5: p.359-386]. A summary of the results is listed in Table VII. The results of the analysis may serve to answer questions concerning the existence of effects or interactions. The three relevent questions relate to column(Defender Tactics), row(Attacker Tactics), and interaction effects.

TABLE VI

ANALYSIS OF VARIANCE DATA

		DEFENDER TACTICS (j) 1	2
ATTACKER TACTICS (i)	1	60 80 70	82 74 84
	2	86 90 94	90 76 92

The null and alternative hypotheses on the interaction effects are stated as

HO: There is no interaction effect($\psi_{ij} = 0$)

HA: There is an interaction effect($\psi_{ij} \neq 0$)

Where "i" and "j" go between levels one and two. If the null hyposthesis (HO) is indeed true then the test statistic, TS = MSI/MSE, is distributed as an "F" with (1 , 8) degrees of freedom. The probability that an "F" variable will exceed the computed value of the test statistic is used to determine if the null hypothesis will be accepted or rejected. It is customary to reject Ho if this computed probability is less than a preselected value, α , called the level of significance. α represents the probability that the null hypothesis is rejected given that it is in fact true. This relationship is depicted in Figure 2.2. For example, if the value of the test statistic is equal to 2.67 or greater, it would lead to a rejection of the null hypothesis at an alpha of .1407. At an alpha of 0.1, we would fail to reject the null hypothesis; it would then be concluded that there is no evidence to suggest the existence of a significant interaction effect.

TABLE VII

RESULTS OF ATTACKER TO DEFENDER TACTICS ANOVA

(HYPOTHETICAL EXAMPLE)

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	TEST STATISTIC	TAIL PROB
MEAN EFFECT	SSM= 79707	1	MSM= 79707	1449.22	0.0000
ATTACKER TACTIC	SSA= 507	1	MSA= 507	9.22	0.0162
DEFENDER TACTIC	SSD= 27	1	MSD= 27	0.49	0.5034
INTERACTION EFFECT	SSI= 147	1	MSI= 147	2.67	0.1407
ERROR EFFECT	SSE= 440	8	MSE= 55		

When the null hypothesis is not rejected, the error sum of squares in the analysis of variance table(Table VIII) is often modified by adding the interaction sum of squares to it; the modified error mean square is then used to test the hypothesis on the main effects. The resulting mean square values and the values of the test statistic are shown in Table VIII. If α = 0.1 one can conclude as depicted in Figure 2.3 that "Attacker Tactics" has a significant effect on the mean time to detect a target by the defender while the "Defender Tactics" does not. Of course, this example was contrived for illustrative purposes and does not necessarily reflect reality. Once the data is collated it will be possible to perform a similar analysis on all the response variables using the ANOVA configurations in Table V.

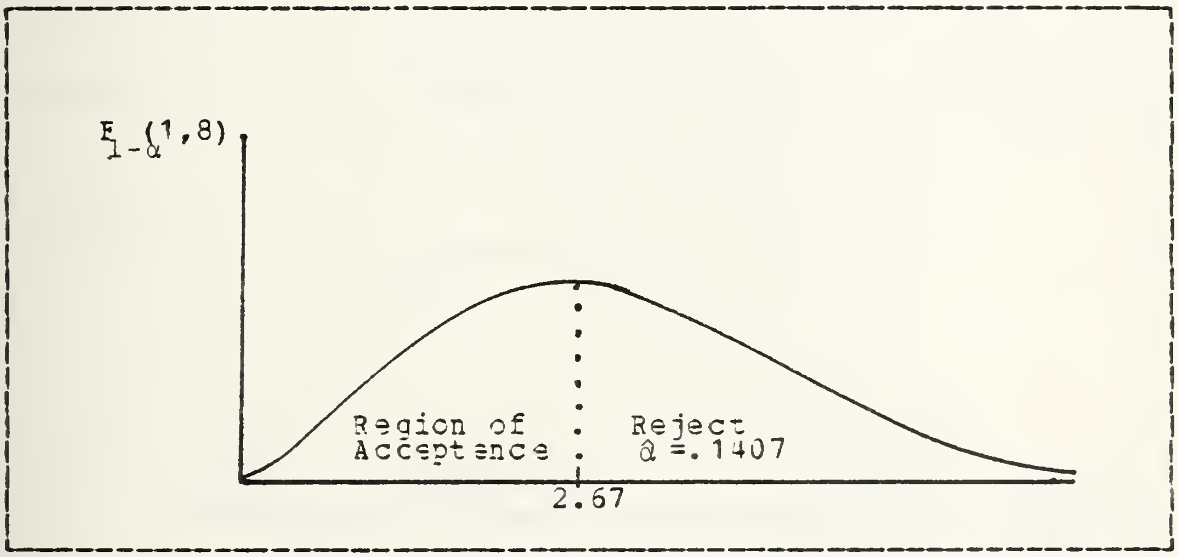


Figure 2.1 Critical Region for the F Statistic.

TABLE VIII

RESULTS FOR POOLED SUM OF SQUARES

$$
\begin{aligned}
MSP &= (SSE + SSI)/(DFe + DFi) \\
&= (440 + 147)/(8 + 1) \\
&= 65.22
\end{aligned}
$$

$$
\begin{aligned}
FA &= MSA/MSP \qquad\qquad F_{.9}(1,9) = 3.36 \\
&= 507/65.22 \\
&= 7.77
\end{aligned}
$$

$$
\begin{aligned}
FD &= MSD/MSP \qquad\qquad F_{.9}(1,9) = 3.36 \\
&= 27/65.22 \\
&= .414
\end{aligned}
$$

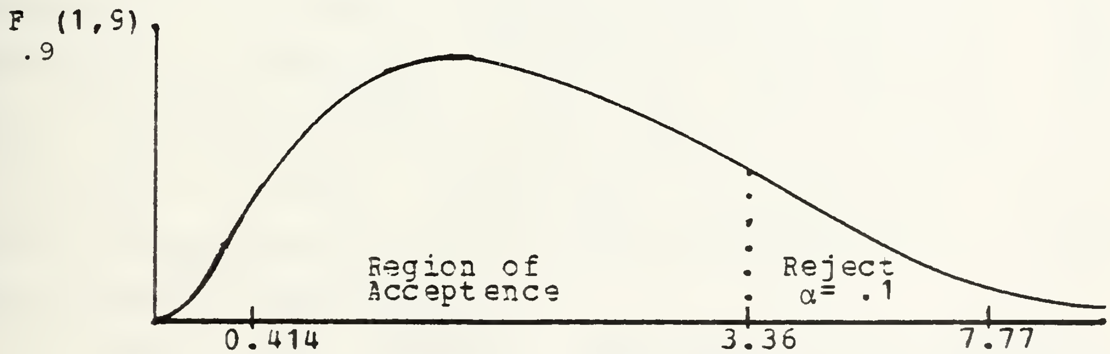


Figure 2.2 Critical Region for $F_{.9}(1,9)$.

III. DATA ANALYSIS

A. GENERAL

The manner and method by which data is analyzed is most often determined by its intended use. If it is to be used for the express purpose of assessing the probability that an event will occur, it would be desirable , at a minimum, to tabulate the results based upon the empirical distribution. On the other hand, if the data is intended to be used for further analysis, it would be more desirable to fit a theoretical distribution to the data. The latter method has some distinct advantages over the former. Tabulation of empirical results are not as versatile as the fitting of a distribution. The fitted distribution allows for the study of the effect of changes in the values of both the parameters and the independent variables. This aspect is especially important in combat modeling which must be responsive to a variety of scenarios and situations. More importantly, theoretical probabality distributions, have been extensively studied, and their properties are well known. This makes them extremely useful in analysis as well as modeling. In many situations, a problem may be more easily modeled mathematically than by laboring over an elaborate computer simulation.

in light of the preceding discussion, the remainder of this chapter will cover the methodology for fitting theoretical distributions to data and testing for goodness-of-fit.

B. DATA STRUCTURE AND CATEGORIZATION

Before any attempt is made at analysis, it is necessary to determine the appropriate level of data to be used. Figure 3.1 provides the data structure for the ARCOMS II experiment. Since the appropriate level of data is dependent upon the issues and analyses to be performed, its determination will be made in conjunction with the discussion of analysis techniques.

C. FITTING THEORETICAL DISTRIBUTIONS TO DATA

1. Methodology

The methodology for fitting probability distributions follows the sequence shown in Figure 3.2. The process begins with an educated guess as to the underlying distribution of the data. The parameters of the hypothesized distribution are either known in advance or they are estimated from the data. The empirical distribution (histogram) is then compared with the hypothsized distribution using a "goodness of fit" test. This will determine if the fitted distribution provides an acceptable approximation to the distribution of the data.

a. Estimating Parameter Values

Once a decision has been made as to the distribution to be fitted, e.g. exponential, gamma, normal etc., it will be necessary to estimate the parameters. The parameters determine the specific shape of the curve. Often estimates of the parameters are available from historical experience. If this is not the case, the data itself may then serve to derive an estimate for the parameters. The appropriate estimates for many of the standard distributions may be found in Reference 6.

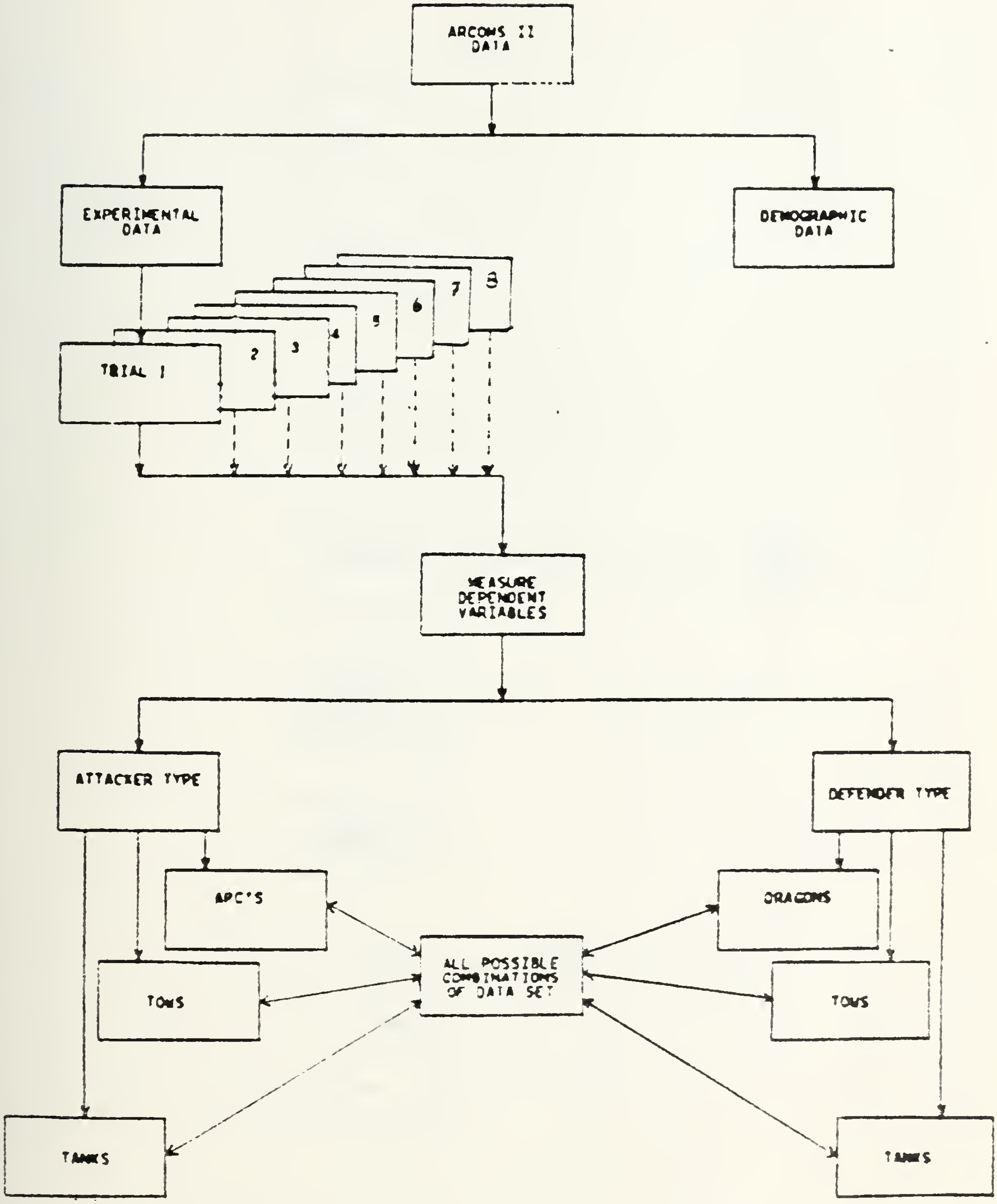


Figure 3.1 Data Structure.

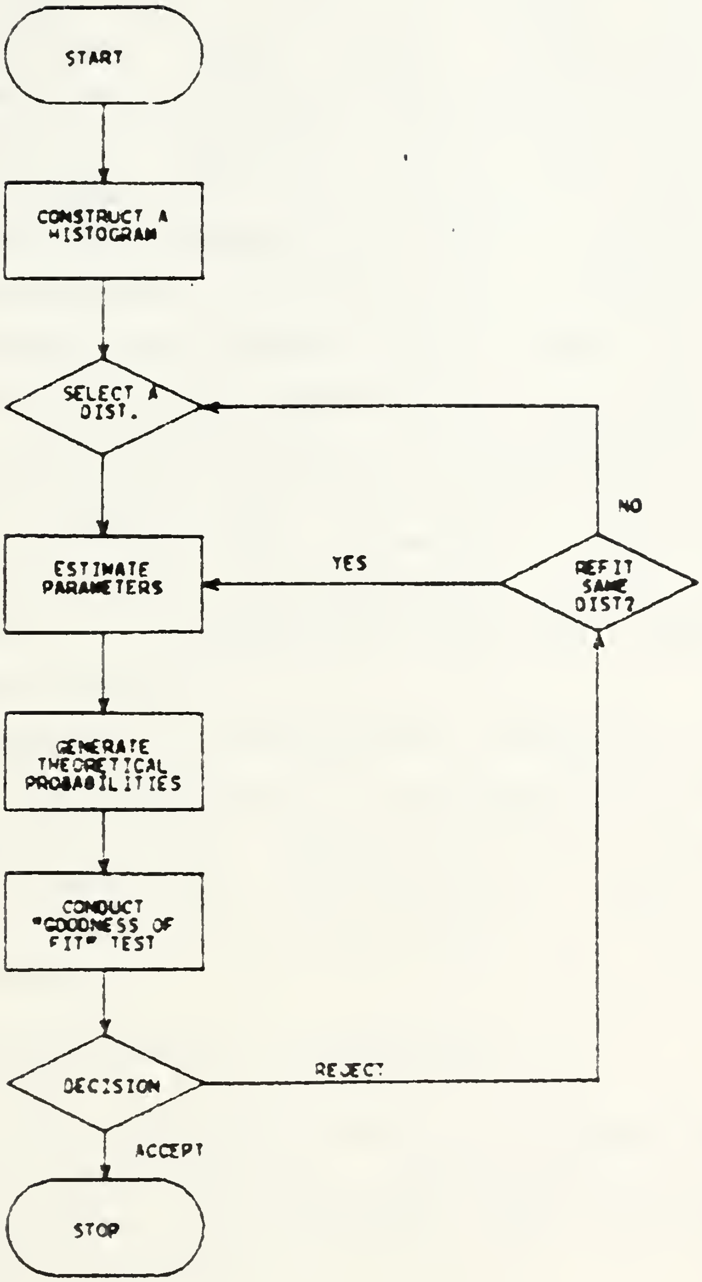


Figure 3.2 Fitting Procedure.

b. "Goodness of Fit" Tests

Two of the most widely used statistical tests for goodness-of-fit are the Chi Square and the Kolomogorov-Smirnov(K-S) tests. Under certain conditions, each of these tests has attributes which makes it preferable to the other. The K-S test may only be used for fitting continuous distributions when the parameters of the distribution to be fitted are assumed to be known. However, for the normal and exponential distributions, special tables have been constructed which permit the K-S test to be used when the parameter have been estimated from the data. This extension of the K-S test is known as the Lilliefors test. The K-S and Lilliefors test are often preferred over the Chi Square test when the sample size is small. The Chi Square test, on the other hand, is applicable to all types of distributions, and it is especially good when moderate to large samples are available.

A useful but less rigorous method of fitting distributions is the technique of constructing probability plots. This graphical method requires plotting the percentiles of the theoretical distribution against the percentiles of the empirical distribution. A straight line plot indicates a good fit.

c. Variables Selected for Analysis

While data analysis should be accomplished on every dependent variable measured, the Conditional Line of Sight(CLOS), Acquisition, and Engagement data were selected to provide procedural examples.

2. CLOS Data

The Conditional Line of Sight data consisted primarily of the time duration and path segment length over which line of sight between an attacker vehicle and at least one element of the opposing force was determined to exist. The time segment duration was measured for both the attacker to defender and defender to attacker categories. The path segment lengths, on the other hand, were measured only for the distance over which the attacker vehicle traveled. This is due to the fact that the attacker forces were moving throughout the entire period of the engagement, whereas, the defender forces would only be expected to move between alternate defensive positions. For this reason it was decided to fit theoretical distributions to the CLOS data between attacker vehicle types (Tanks, Tows, and APCs), and the aggregate of all the defender forces.

Histograms of the data sets indicate that the CLOS Time and Path segment lengths might be represented by one of five distributics. They are the Exponential, Gamma, Weibull, Beta and Lognormal distributions. By varying the parameters of these distributions, it is possible to obtain a curve that is "similar" in shape to that of the histograms. The Exponential, Gamma, and Weibull distributions were fit to the time and path segment lengths. Table IX shows the results of this fit for two of these sets. Since the number of data points in each of the two sets is 829, the Chi Square test was used to compute the test statistic, X^2. By comparing X^2 to the $1-\alpha$ quantile of the Chi Square distribution the following rejection criteria may be used. Reject the null hypothesis of a "good fit" if

$$X^2 > \chi^2_{1-\alpha}(D.F.)$$

TABLE IX

RESULTS OF FITTING ATTACKER TANKS CLOS DATA

TYPE	n	CELLS (N)	DIST	PARAMETERS (K)	CHI STAT	D.F. (K-N)	$\chi^2_{1-\alpha}$(DF)
TIME SEG.	829	5	EXP.	λ=.01935	194.1	4	9.488
		5	GAM.	θ=.00686	7.539	3	7.814
				r=.3478			
		5	WEIB.	ν=0.0	5.52	2	5.991
				α=31.514			
				β=.5714			
PATH SEG.	829	7	EXP.	λ=.0118	688.4	6	12.59
		7	GAM.	θ=.0027	2.407	5	11.07
				r=0.231			
		7	WEIB.	ν=0.0	8.67	4	9.488
				α=44.505			
				β=.5128			

A comparison of the test statistic to the .95 quantile of the Chi Square distribution, showed that for all time segment lengths the hypothesis that the data represents an exponential distribution is soundly rejected. However, both the Gamma and the Weibull distributions provide good fits. For path segment lengths the Gamma distribution provided an obviously better fit than did the Weibull distribution. The only exception to this is the Tow path segment lengths. Figure 3.3 shows the plots of the Weibull cummulative distributions function and the empirical CDF for tank time and path segment data. For Time Segment lengths

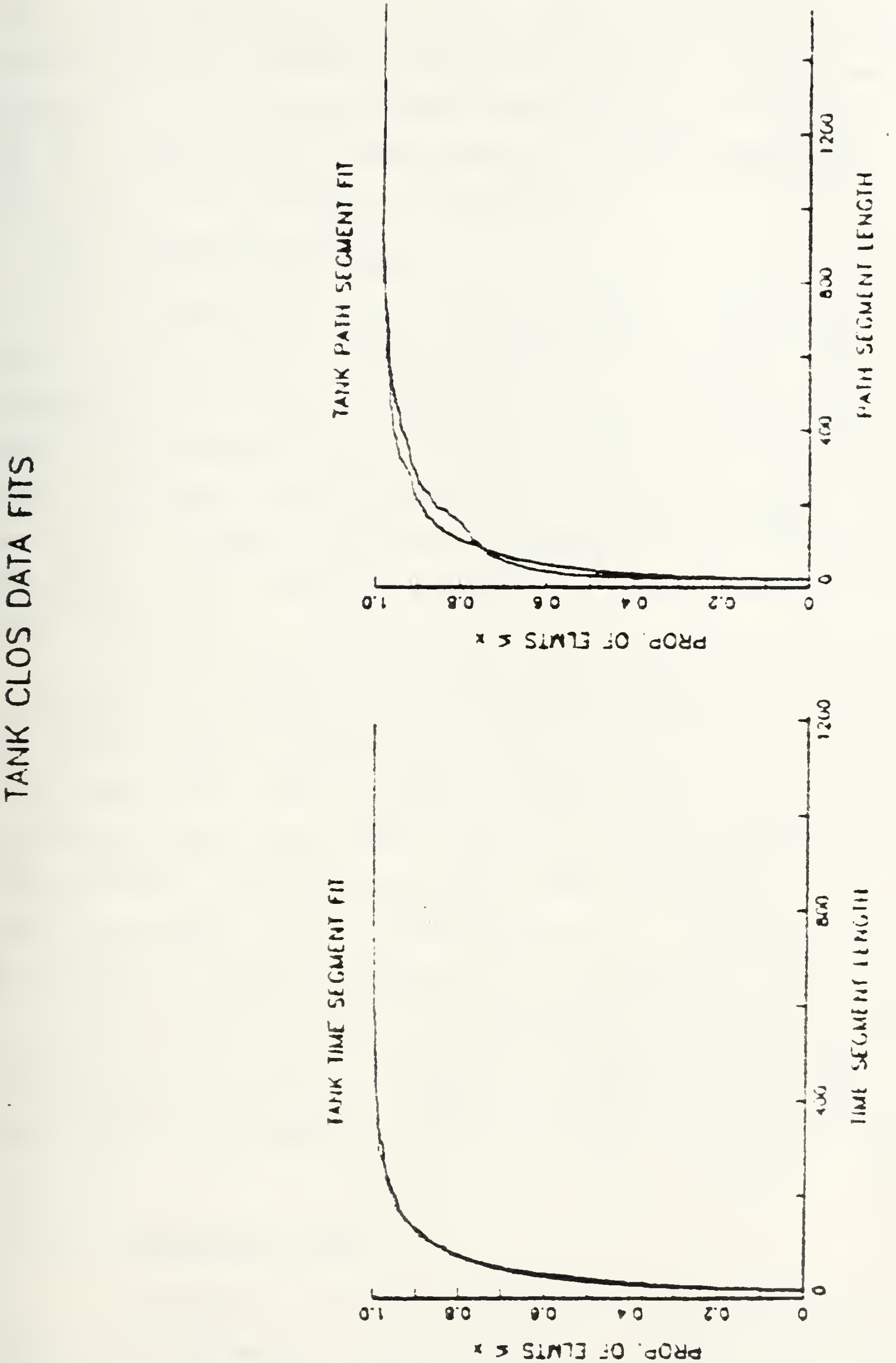


Figure 3.3 Fitted and Empirical CDF Plots.

the two distributions are virtually identical. This indicates that the Weibull provides a good fit for Time segment lengths. In the second case the Weibull fit was not as good as the Gamma fit. The results for the remaining sets of CLOS data are enclosed as Appendix C.

3. Acquisition Data

Acquisition data was devided into two data groups. The Attacker weapons acquiring or engaging those of the Defender force, and the Defender force weapons acquiring and engaging Attacker weapon types. From this data, two dependent variables were selected for analysis viz., "Time to Acquire" a target given that there exists conditional line of sight, and "Time to Engage" a target given that it has been acquired.

The histograms for both "Time to acquire" and "Time to engage" pointed to the exponential distribution as the one most likely to provide a good fit. In those cases where the data sets had a small number of data points, the Lilliefors test was used. The Lilliefors quantiles for the exponential distribution have been tabulated and may be found in Table A16 of Reference 7. The results Tanks acquiring or engaging Defender Tow weapons is shown in Table X. They indicate that the exponential distribution provides a good fit to both the data on "Time to Acquire" and for Attacker the 'Time to Engage". These results as well as those for the remaining data sets are provided in Appendix C.

4. Engagement Data

Engagement data consists of measurements on the range to engagement, aim errors in both vertical and horizontal angular shifts originating from the target's center

TABLE X

GOODNESS-OF-FIT RESULTS FOR ACQUISITION DATA

ATTACKER TANKS TO DEFENDER TOWS

TYPE	n	DIST	PARAMETERS	TEST STAT	CRITICAL VALUE
Time to Acq.	15	EXP.	λ =.0092	.1642	$\hat{\alpha}$ < 0.5
Time to Eng.	15	EXP.	λ =.0815	.3202	$\hat{\alpha}$ < .999

of mass, as well as a series of indicator variables delineating target exposure, aspect angle, whether it is moving, whether it is firing, and whether it was hit, missed or killed. Since all the variables, except for aim errors, are indicator in nature, they will merely yield a proportional figure of the number of times they occur in the data. Consequently, aim errors are the only dependent variables selected for fitting a distribution.

An examination of this data revealed that aim errors were only recorded for Attacker and Defender Tank weapons. The data was, therefore, formed into four sets corresponding to the "X" and "Y" coordinates of aim error for Attacker and Defender Tanks. Histograms for each of these coordinates suggested that a Normal distribution is a likely candidate to fit. Since the aim error distribution is bi-variate, a bi-variate normal distribution must be fit, unless it can be shown that the correlation between the two coordinates is zero. The correlation between "X" and "Y" for Attacker and

Defender Tanks were computed to be 0.15 and -0.04 respectively. These values are appear to be small enough to assume that the correlation between the two variables is zero. With this assumption the "X" and "Y" coordinates can be handled separately.

The results of the Chi Square test listed in Table XI show that the Normal distribution does not provide a good fit to the data. While they are similar in shape (bell shaped), the empirical distribution is extremely "peaked" when compared to the theoretical Normal distribution. Further investigation of the data showed this was due to a large number of zero error points within the data set. This excessive number of zero aim errors may be the result of rounding to the nearest integer mil when the data was recorded. Since the significance of a one mil error depends upon the range to the target, measuring to the nearest mil might provide far too coarse a measurement scale. The end result is a clustering of data points on the integer values, especially at zero. As a consequence it was not possible to obtain a good fit to the aim error data.

TABLE XI

RESULTS OF AIM ERROR FITS

DATA SET	NUMBER OF CELLS	PARAMETER ESTIMATES	CHI SQ. VALUE	DEGREES OF FREEDOM
Attacker (X-coord)	5	$\mu = -0.331$ $\sigma^2 = 1.01$	61.75	3
Attacker (Y-coord)	5	$\mu = 0.053$ $\sigma^2 = 0.982$	80.67	3
Defender (X-coord)	4	$\mu = .0167$ $\sigma^2 = .572$	111.385	2
Defender (Y-coord)	6	$\mu = .428$ $\sigma^2 = 1.09$	294.564	4

IV. METHODS FOR DEALING WITH QUESTIONS OF SIGNIFICANCE

A. GENERAL

In order to improve combat modeling within the Army an increased understanding of the combat process is essential. Without the knowledge of how combat units operate, manuever, engange one-another, or terminate engagments, combat modeling could scarcely be expected to represent reality. Thus, the primary focus of this chapter will be to discuss those analysis methods which may be utilized to provide answers to questions regaring the significance of certain combat processes. The questions to be examined are based upon the issues that TRASANA determined to be important. Each question will be addressed separately, by briefly discussing the pertinent issue, the most appropriate method of analysis, and the experimental data that will support the analytical method.

B. THE EFFECT OF BOUNDING BY THE DEFENDER ON HIS DETECTABILITY

It has, for the most part, been assumed that if a defender were to stealthily move between alternative defensive positions, he might prolong the time it takes to detect him. A counter argument is that any movement against a stationary backgroud is more likely to queue the visual, thermal, or electronic detection ability of the searcher, and thereby, increase the probability that the attacker detects a defender target. The question is then, "Does the Defender movement into and between alternate firing positions significantly increase the rate at which the Attacker force is able to detect him?"

The question may be viewed as asking whether the data supports the notion that as the number of moves between alternate positions increases so does the the number of detections. An approach to answering this question is to test the statistical hypotheses that no increasing trend exists versus the alternative that an increasing trend does exist.

The data required must relate the number of times that each defender vehicle moves between defensive positions to the corresponding the number of times that he is detected by any member of the attacker force. A set of data for each trial will consist of the paired observation (Xj, Yj), where Xj is the number of moves for the jth defender vehilce, and Yj is the total number of detections scored against him.

A nonparametric method for detecting increasing or decreasing trends is the Cox-Stewart test [Ref. 7: pp. 133-139]. Although this test is adequate for determining whether or not a trend exists, it provides no specific information as to how this result is to be used for modeling or analysis. It is, therefore, more useful to employ a method which will, in addition to answering the question, also provide an estimate of the magnitude of the relationship between the two variables of interest by means of nonparametric regression [Ref. 7: pp. 272-277]. Assuming the linear regression model

$$Yj = A + BXj \tag{4.1}$$

first the nonparametric estimates of "A" and "B" based on ranks are determined; an estimate of the number of detections may be obtained by substituting these estimates in (4.1). The slope "B" in (4.1) will determine whether or not a relationship exists between Xj and Yj. The magnitude and

sign of the slope will determine the degree and direction of the relationship. The Spearman's Rho test for correlation [Ref. 7: pp. 252-256] may be used to test the following hypothesis

Hc: $b = bo$

Ha: $b > bo$

This is equivalent to testing the null hypotheses that no correlation exits versus the alternative that positive correlation does exist. A rejection will indicate that a correlation does indeed exist. It must be pointed out that a regression using least squares could be used, provided that all the distributional assumptions are satisfied. However, least squares regression is extremely sensitive to the existence of outliers. If it is suspected that outliers are present, it is best to use a more "robust" method of regression. such as the one just described or the Median regression.

A confidence interval for the slope in equation 4.1 may be derived by using the "two point" slope method [Ref. 7: p 266-267].

C. QUICK DASHES BY ASSAULTING VEHICLES

In order to reduce vulnerability, assaulting vehicle make quick dashes from one defilade position to the next. It is suspected that these quick dashes reduce its ability to detect defender targets. Therefore, the following question is asked, " Do quick dashes by assaulting weapons significantly reduce their ability to detect defender targets?"

As in the previous section we may test for increasing trend using the Cox-Stewart test; or perform a hypothesis test on the slope of the regression to determine if a positive correlation exists. Because of the advantages prvicusly

enumerated, the nonparametric regression method is preferred in this analysis as well.

In either case the data sets are constructed in precisely the same manner. Care must be taken to insure that the length of a "quick dash" is precisely defined and that it is consistent with current tactical doctrine. Assuming that the quick dash length is 200 meters, it is now possible to define Xj, the number of times that vehicle "j" moved less than or equal to 200 meters; corresponding to Xj, we may now determine the number of detections scored by vehicle "j". The result is the bi-variate data set (Xj,Yj). This type of data may be collected specific to a particular battle run, trial or aggregatted for the entire experiment.

D. ENGAGEMENT AND ITS SIGNIFICANCE ON ATTRITION

The question here is "Does the frequency with which engagements occur hurt the defender more than the attacker?", or "Does the frequency with which a force engages the opposing force increase the kills it achieves and decreases the kills it receives?"

For either the defender or attacker force, two sets of bi-variate data must be analyzed. One set is the number of engagements initiated by that force (Xi) and the number of kills attributed to it (Yi). The other set is the number of engagements initiated by that force(Xi) and the number of kills it receives(Zi). Each battle run represents one sample point. A total of 24 sample points may, therefore, be derived. The analysis procedure is the test for trend using the Cox-Stewart test, or the method of nonparametric regression discussed in section B.

E. ROUNDS EXPENDED ON TRUE VERSUS FALSE TARGETS

The issue to be addressed is whether there exists a relationship between the number of rounds expended against true or a false targets. From the stand point of the Attacker force, the question can be posed "Do Attacker weapons fire fewer rounds per target against false targets than against true ones?" The same question may in turn be asked with respect to the Defender force. It may, in addition, be more detailed in scope so as to concern a particular weapon type, battle run, or trial number.

The issue involves a comparison of the distribution of two sets of data. We are specifically interested in determining whether or not we can expect one set to have higher expected value than the other.

The data required for this analysis consists of two sets of observations. One set representing the number of rounds expended against true targets (Sj). The other set is the number of rounds expended against false targets (Sk), where j=1,...n1 and k=1,...,n2. The set of hypotheses are:

Ho: The expected value of Sk is greater than or equal to the expected value of Sj. $\{E(Sk) \geq E(Sj)\}$

Ha: The expected value of Sk is less than the expected value of Sj. $\{E(sk) < E(Sj)\}$

An appropriate test is the Mann-Whitney nonparametric test for two independent samples [Ref. 7: pp. 215-223]. The procedure consists of first pooling the two samples and assigning a rank to each observation; the test statistic is the sum of the ranks assigned to Sj (or Sk). Appropriate tables of critical values are in APPENDIX A of Reference 7.

F. FALSE TARGET DETECTION RATE

It is suspected that the detection of false targets can easily occur in a batlle-field environment. It is, therefore, critical to the understanding of this process, to determine the significance of a comparison between the rates of detection of false targets for Defender weapons, Attacker Assaulting weapons and Attacker Overwatching weapons. The question is asked, " Is the false target detection rates the same for the Attacker Overwatching weapons, the Defender weapons, and the Assaulting weapons?"

Assuming independence between and among the three samples, a test on the equality of distributions may be performed. The hypotheses are:

Ho: All three population distribution functions are identical.

Ha: At least one of the populations tends to yield larger observations than the others.

Two nonparametric methods of testing for significance were considered viz., the Kruskal-Wallis test for several independent samples [Ref. 7: pp. 229-237], and the Van Der Waerden test for several independent samples [Ref. 7: pp. 317-326]. While the Kruskal-Wallis test statistic is based upon ranks, the Van Der Waerden is based upon the concept of normal scores. The Van Der Waerden test has an advantage in that it has a higher Asymptotic Relative Efficiency than the Kruskal-Wallis Test. In this respect the Van Der Waerden test is comparable to its parametric counterparts, the "t" and "F" tests, and has the same asymptotic efficiency as the parametric tests when the population is really normal and a larger asymptotic efficiency when the population is nonnormal [Ref. 7: pp. 316-317]. For this reason the Van Der Waerden test was selected as the better of the two alternatives for testing the stated hypotheses. An initial

comparison of the three populations will either accept or reject the hypothesis of identical distributions. If the test fails to reject we are spared from having to conduct individual comparisons between the samples. If, on the other hand, a rejection occurs the test provides an easy method for making individual comparisons. Pairwise comparisons are performed in order to determine which sets are significantly different from one-another. The unique pairs are Defending to Assaulting forces, Assaulting to Overwatching force, and Defending to Overwatching forces. The magnitude of the difference will then determine how they are to be ordered. It is this ordering that will provide the final answer.

The data required for this test consists of the rate of detection for each of the three types of samples. Rate of detection is computed by deviding the number of false target detections by the period of time in which the detections were made. Data sets may be constructed based upon an individual trial or aggregated.

G. FREQUENCY OF OVERWATCHER DETECTIONS

A firing target generates a number of detectable effects such a blast, flash, and smoke which serve to queue a searcher. It is suspected that this queuing may significantly enhance the Overwatcher's ability to detect targets. Therefore, the relevent question for this analysis is stated as, " Do stationary Attackers, or Overwatchers incur a higher frequency of detection when they are firing versus when they are not?"

The question implies that an evaluation must be made to determine if the a firing overwatcher experiences a greater proportion of detections than does a nonfiring Overwatcher. If Xi represents the number of detections when the

Overwatcher is firing and Yi represents the number of detections when the Overwatcher is not firing, a bivariate data point may be assigned to each weapon of the Overwatching force. If we let Pf represent the proportion of detections incurred when an Overwatcher is firing and Pn represent the proporting of time he is not firing, the following hypotheses may be stated

Ho: Pf = Pn

Ha: Pf > Pn

The hypotheses may be tested by constructing a standardized normal test statistic [Ref. 8: pp. 378-384]

$$Z = \frac{(Pf - Pn) - 0.0}{\sqrt{\dfrac{Pf(1-Pf)}{Nf} + \dfrac{Pn(1-Pn)}{Nn}}} \qquad (4.2)$$

A rejection occurs if the test statistic exceeds the Z quantile of the standard normal distribution. A confidence interval may now be established for (Pf-Pn) as

$$0.0 < Pf - Pn < Z_{1-\alpha}\sqrt{\frac{Pf(1-Pf)}{Nf} + \frac{Pn(1-Pn)}{Nn}} \qquad (4.3)$$

For each Overwatching , or stationary attacker target a bivariate data point is constructed. The elements of the bivariate point are Xi, the number detections when the target is firing, and Yi, the number of detections when the target is not firing. The proportions Pf and Pn are then Pf= Xi/(Xi+Yi) and Pn= Yi/(Xi+Yi). The sample may be constructed for each battle run, trial or as an aggregation of the entire experiment.

V. CONCLUSIONS AND RECOMMENDATIONS

A. CONCLUSIONS

While the ARCOMS II field experiment forged the way in the collection of experimental data on the Armor Combat processes, it did not provide for an efficient analysis of experimental effects and interactions. The choice of the eight factor-level combinations at which the data was measured failed to provide the balance needed to perform a 2^{4-1} fractional factorial analyis. The only model which could be used is the 2^2 factorial analysis with replications. Even this is not an applicable sub-model for all factor combinations. In fact, there are only three combinations of factors that provide suitable models. They are Attacker Tactics to Defender Tactics, Attacker Tactics to Terrain, and Attacker Tactics to Hatch Position.

The fitting of theoretical distributions is possible for a great deal of the data. Preliminary data analysis suggests that CLOS time and path segment lengths are distributed as either Gamma or Weibull distributions while the time to aquire and time to engage appear to be exponentially distributed.

B. RECOMMENDATIONS

Based upon these conclusions the following recomendations are made.

1. An Analysis of Variance for the dependent variables listed in Appendix A should be accomplished using a 2^2 factorial design(2x2 ANOVA) with three replications per cell. This model is provided in Appendix B. The Model assumptions should be verified by

checking for normality of the error terms. If this assumption is not reasonable, consideration should be given to the Friedman nonparametric analysis of variance and its extension for the case with replications [Ref. 7: pp. 299-308].

2. For future experimentation, it is recommended that a detailed experimental design be determined prior to collecting any data. The design should specify the issues to be addressed, the analysis techniques to be employed, and how the data is to be structured to support the analysis. An early identification of the analysis techniques will help define the type and quantity of data to be collected.
3. The CLOS Time segment lengths when ploted against both Time to Clos and Range to the initiation of CLOS reveal the presence of a bi-modal relationship. When plotted against the range to initiation of CLOS the modes, representing longer duration as well as more frequent occurrences, were located at 1500 and 3000 meters. This phenomenon occurred for both Time and Path segment lengths. Figures showing this phenomenon are in Appendix D. It is recommended that an investigation of this phenomenon be pursued with small scale experiment.

Prior to the ARCCMS experiment, there has been very little data generated from field experimentation which can represent a realistic combat scenario. Combat models have relied heavily upon engineering and historical data. Engineering data is generated from well controlled "laboratory-like" experimentation. The interactions involved in a combat evironment with a free flowing force-on-force engagement are not reflected in such data. Some idea must be obtained as to how different data from field experimentation is from engineering or historical data. The objective

is to determine if the field experimentation data provides a more realistic representation of the combat data than the other two. It is reccommended that

1. A comparative analysis be performed between the ARCOMS data and that of the Balistic Research Laboratory and the Night Vision Laboratory.
2. A Regression Analysis should be performed using the engagement data discussed in Chapter III to predict the parameter for probability of detection in time "t". This should be compared with the results of the Night Vision Laboratory experiment. This comparative analysis may provide an insight into the differences between engineering data and that collected from field experimentation.

APPENDIX A
DEPENDENT VARIABLES

The dependent variables are listed according their contribution to combat processes in

A. OFFENSIVE OPERATIONS

Attacker vehicle LOS time and path Segments.

Number of Defensive position scanning lasers with LOS to single attacker vehicle.

Number of attacker vehicles with LOS to single defensive position scanning laser.

Defender vehicle CLOS time and path segments during exposure.

Number of defender vehicles with CLOS to single attacker vehicles.

Number of targets acquired by the attacker force.

Time to acquire true targets by the attacker.

Number of false targets acquired by the attacker.

Number of true targets with CLOS and rounds expended by the attacer force.

Number of true targets engaged by the attacker force.

Time to engage true targets by the attacker.

Target engagement results for true target engagement by the attacker force.

Number of false targets engaged by the attacker force.

Time to engage false targets by the attacker force.

Reported target engagement results for false target engagements by the attacker force.

Time, distance, and movement rate between bound positions for the attacker force.

Time of occupation of the bound position and rounds fired by the attacker force.

Number of hits received by attacker vehicles.

Number of kills of attacker vehicles.

B. DEFENSIVE OPERATIONS

Defender vehicle LOS time segments.

Mean number of defender vehicles with LOS to offensive scanning lasers.

Attacker vehicles with CLOS time and path segments during exposure.

Number of attacker vehicles with CLOS to single defender vehicles.

Number of true targets acquired by the defender forces.

Time to acquire true targets by defender vehicles.

Number of false targets acquired by the defender forces.

Number of true targets with CLOS and rounds expended by the defender forces

Number of true targets engaged by the defender force.

Time to engage true targets by defender vehicles.

Target engagement results for true target engagements by the defender forces.

Number of false targets engaged by the defender force.

Time to engage false targets by the defender vehicles.

Reported target engagement results for false target engagements by the defender force.

Time, distance, and movement rate between bound positions for the defender force.

Time of occupation of the bound position and rounds fired by the defender force.

Number of hits received by defender vehicles.

Number of kills of defender vehicles.

APPENDIX B
2X2 ANOVA WITH REPLICATIONS

A. ANOVA MODEL

The 2x2 analysis of variance model with three replications per cell is

$$Y_{ijk} = \eta + \beta_i + \gamma_j + \psi_{ij} + \varepsilon_{ijk}$$

where $i = 1,\ldots,n$; $n=2$
$j = 1,\ldots,m$; $m=2$
$k = 1,\ldots,p$; $p=3$

The model parameters are

η = the grand mean
β_i = the first factor effect
γ_j = the second factor effect
ψ_{ij} = the interaction effect
ε_{ijk} = the error term

This model assumes that the error terms are independent and Normally distributed with a mean of zero and variance of σ^2. It may be used to test the following hypotheses

1. All β_i = 0. (There is no effect due to the first factor)
2. All γ_j = 0. (There is no effect due to the second factor)
3. All ψ_{ij} = 0. (There is no interaction effect) The following terms are defined in order to clarify the ANOVA table on the following page.

TABLE XIII

2x2 ANOVA TABLE

SOURCE	D.F.	SUM OF SQUARES	MEAN SQUARE	RATIO MS
FACTOR A	$n-1$	$SSA = mp\sum_{i}^{n}(Y_{i..} - Y)^2$	$MSA = SSA/(n-1)$	MSA/MSE
FACTOR B	$m-1$	$SSB = np\sum_{j}^{m}(Y_{.j.} - Y)^2$	$MSB = SSB/(m-1)$	MSB/MSE
INTERACTION (AB)	$(n-1)(m-1)$	$SSI = p\sum_{i}^{n}\sum_{j}^{m}(Y_{ij.} - Y_{i..} - Y_{.j.} - Y)^2$	$MSI = SSI/(n-1)(m-1)$	MSI/MSE
ERROR	$nm(p-1)$	$SSE = \sum_{i}^{n}\sum_{j}^{m}\sum_{k}^{p}(Y_{ijk} - Y_{ij.})^2$	$MSE = SSE/nm(p-1)$	
TOTAL	$nmp-1$	$TSS = \sum_{i}^{n}\sum_{j}^{m}\sum_{k}^{p}(Y_{ijk} - Y)^2$		

E. COMPUTER PROGRAM

```
FILE: TESTAE     PROGRAM   A1   NAVAL POSTGRADUATE SCHOOL

//DIGIORGI JOB (1928,1159),'DIGIORGI OR 360',CLASS=A
//*MAIN ORG=NPGVM1.1928P
//*
//*        SAMPLE OF ANOVA HYPOTHETICAL TEST DATA
//*
//*        ATTACKER TACTICS TO DEFENDER TACTICS.
//*
//*
//   EXEC BIMED,PROG=BMDP2V
//GO.SYSIN DD *
/PROBLEM     TITLE IS 'ARBITRARY HYPOTHETICAL TEST DATA'.
/INPUT       VARIABLES ARE 3.
             FORMAT IS '(3F3.0)'.
/VARIABLE    NAMES ARE DEFTACT,ATACTIC,DETTIME.
/DESIGN      DEPENDENT IS DETTIME.
             GROUPING ARE DEFTACT,ATACTIC.
/GROUP       CODES(1) ARE    1,      2.
             NAMES(1) ARE DELIB,HASTY.
             CODES(2) ARE        1,      2.
             NAMES(2) ARE FIREMVT,RAPID.
        /END
  1   1  60
  1   1  80
  1   1  70
  1   2  86
  1   2  90
  1   2  94
  2   1  82
  2   1  74
  2   1  84
  2   2  90
  2   2  76
  2   2  92
/*
//
```

```
BMDP2V - ANALYSIS OF VARIANCE AND COVARIANCE WITH REPEATED MEASURES.
BMDP STATISTICAL SOFTWARE, INC.
1964 WESTWOOD BLVD. SUITE 202
(213) 475-5700
PROGRAM REVISED APRIL    1982
MANUAL REVISED -- 1981
COPYRIGHT (C) 1982 REGENTS OF UNIVERSITY OF CALIFORNIA

TO SEE REMARKS AND A SUMMARY OF NEW FEATURES FOR
THIS PROGRAM, STATE NEWS. IN THE PRINT PARAGRAPH.

     JUNE 16, 1983  AT 22:23:08

PROGRAM CONTROL INFORMATION

/PROBLEM     TITLE IS 'ARBITRARY HYPOTHETICAL TEST DATA'.
/INPUT       VARIABLES ARE 3.
             FORMAT IS '(3F3.0)'.
/VARIABLE    NAMES ARE DEFTACT,ATACTIC,DETTIME.
/DESIGN      DEPENDENT IS DETTIME.
             GROUPING ARE DEFTACT,ATACTIC.
/GROUP       CODES(1) ARE     1,      2.
             NAMES(1) ARE DELIB,HASTY.
             CODES(2) ARE      1,      2.
             NAMES(2) ARE FIREMVT,RAPID.
     /END

PROBLEM TITLE IS
ARBITRARY HYPOTHETICAL TEST DATA

NUMBER OF VARIABLES TO READ IN. . . . . . . . . .          3
NUMBER OF VARIABLES ADDED BY TRANSFORMATIONS. .            0
TOTAL NUMBER OF VARIABLES . . . . . . . . . . . .          3
NUMBER OF CASES TO READ IN. . . . . . . . . . . . TO END
CASE LABELING VARIABLES . . . . . . . . . . . . .
MISSING VALUES CHECKED BEFORE OR AFTER TRANS. . NEITHER
BLANKS ARE. . . . . . . . . . . . . . . . . . . . MISSING
INPUT UNIT NUMBER . . . . . . . . . . . . . . . .          5
REWIND INPUT UNIT PRIOR TO READING. . DATA. . .           NO
NUMBER OF WORDS OF DYNAMIC STORAGE. . . . . . .        96254
NUMBER OF CASES DESCRIBED BY INPUT FORMAT . . .            1

VARIABLES TO BE USED
     1 DEFTACT       2 ATACTIC       3 DETTIME

INPUT FORMAT IS
(3F3.0)

MAXIMUM LENGTH DATA RECORD IS     9 CHARACTERS.

I N P U T   V A R I A B L E S . . . . .
  VARIABLE       RECORD    COLUMNS     FIELD  TYPE                 VARIABLE
INDEX   NAME       NO.   BEGIN  END    WIDTH                      INDEX   NAME
----- --------   ----  ----- -----   -----  ----                 ----- --------
    1 DEFTACT       1      1     3      3    F                        3 DETTIME
    2 ATACTIC       1      4     6      3    F

DESIGN SPECIFICATIONS

        GROUP =    1    2
        DEPEND =   3

BASED ON INPUT FORMAT SUPPLIED    1 RECORDS READ PER CASE.

                                                                   INTERVAL
 VARIABLE       MINIMUM  MAXIMUM  MISSING CATEGORY CATEGORY   GREATER LE
 NO. NAME        LIMIT    LIMIT    CODE     CODE     NAME       THAN     C

   1 DEFTACT
                                         1.00000 DELIB
                                         2.00000 HASTY
   2 ATACTIC
                                         1.00000 FIREMVT
                                         2.00000 RAPID
```

C. OUTPUT OF ANOVA RESULTS

```
PAGE    2  BMDP2V ARBITRARY HYPOTHETICAL TEST DATA

GROUP STRUCTURE

 DEFTACT    ATACTIC     COUNT
 DELIB      FIREMVT       3.
 DELIB      RAPID         3.
 HASTY      FIREMVT       3.
 HASTY      RAPID         3.

          CELL MEANS FOR  1-ST DEPENDENT VARIABLE
                                                              MARGINAL
DEFTACT =  DELIB        DELIB         HASTY         HASTY
ATACTIC =  FIREMVT      RAPID         FIREMVT       RAPID

DETTIME      70.00000     90.00000     80.00000     86.00000     81.50000

COUNT            3            3            3            3           12

STANDARD DEVIATIONS  FOR  1-ST DEPENDENT VARIABLE

DEFTACT =  DELIB        DELIB         HASTY         HASTY
ATACTIC =  FIREMVT      RAPID         FIREMVT       RAPID

DETTIME      10.00000      4.00000      5.29150      8.71780


PAGE    3  BMDP2V ARBITRARY HYPOTHETICAL TEST DATA

ANALYSIS OF VARIANCE FOR  1-ST
DEPENDENT VARIABLE - DETTIME

      SOURCE                     SUM OF     DEGREES OF      MEAN          F       TAIL
                                 SQUARES     FREEDOM       SQUARE                 PROB.

      MEAN                    79707.00000       1       79707.00000    1449.22   0.0000
      DEFTACT                    27.00000       1          27.00000       0.49   0.5034
      ATACTIC                   507.00000       1         507.00000       9.22   0.0162
      DA                        147.00000       1         147.00000       2.67   0.1407
 1    ERROR                     440.00000       8          55.00000

NUMBER OF INTEGER WORDS OF STORAGE USED IN PRECEDING    PROBLEM     1013
CPU TIME USED       0.794 SECONDS
```

APPENDIX C
DATA ANALYSIS RESULTS

A. CLOS DATA

The results of the "goodness of fit" tests for the data on Conditional line of sight is listed in Table XIII. Histograms are provided as Figures C.1, C.2, and C.3.

B. AQUISITION DATA

The results of fitting the Aquisition data is provided in two parts. Table XIV provides the results for "Time to Detect" while Table XV provides the results for "Time to Engage". Rather than include all histogram, three typical histograms are provided as Figures C.4, C.5, and C.6.

C. AIM ERROR DATA

Histograms for aim errors are provided as Figures C.7 and C.8.

D. SCATTER DIAGRAMS FOR TIME AND PATH SEGMENT LENGHTS

Figures C.9 through C.11 show the scatter plots for Time and Path segment lengths against time and range to initiation of conditional line.

TABLE XIII

RESULT OF FITTING CLOS DATA

TIME SEGMENT DATA:

SET	CELLS	DIST.	PARAM.	TEST STAT	D.F.	$\chi^2_{1-\alpha}$ (DF)
TANKS (829)	5	E	λ=.0194	194.1	4	9.488
		G	θ=.0069 r=.3478	7.539	3	7.851
		W	ν= 0.0 α=31.51 β=.5714	5.52	2	5.991
TCWS (188)	7	E	λ=.0100	87.03	6	12.59
		G	θ=.0033 r=.3281	5.512	5	11.07
		W	ν= 2 α=56.03 β=.5405	5.089	4	9.488
APCs (160)	6	E	λ=.026	49.75	5	11.07
		G	θ=.0085 r= .325	7.126	4	9.488
		W	ν= 1 α=21.38 β=.5405	6.395	3	7.851

PATH SEGMENT DATA:

SET	CELLS	DIST.	PARAM.	TEST STAT	D.F.	$\chi^2_{1-\alpha}$(DF)
TANKS (829)	7	E	λ=.0118	688.4	6	12.59
		G	θ=.0027 r=.231	2.407	5	11.07
		W	ν= 0.0 α=44.51 β=.5128	8.67	4	9.488
TCWS (188)	4	E	λ=.0689	90.87	3	7.851
		G	θ=.0069 r=.1325	10.52	2	5.991
		W	ν= 0 α=4.369 β=.04	18.25	1	3.84
APCs (160)	5	E	λ=.0118	53.016	4	9.488
		G	θ=.0044 r= .325	7.282	3	7.851
		W	ν= 0 α =50.78 β =.555	6.278	2	5.991

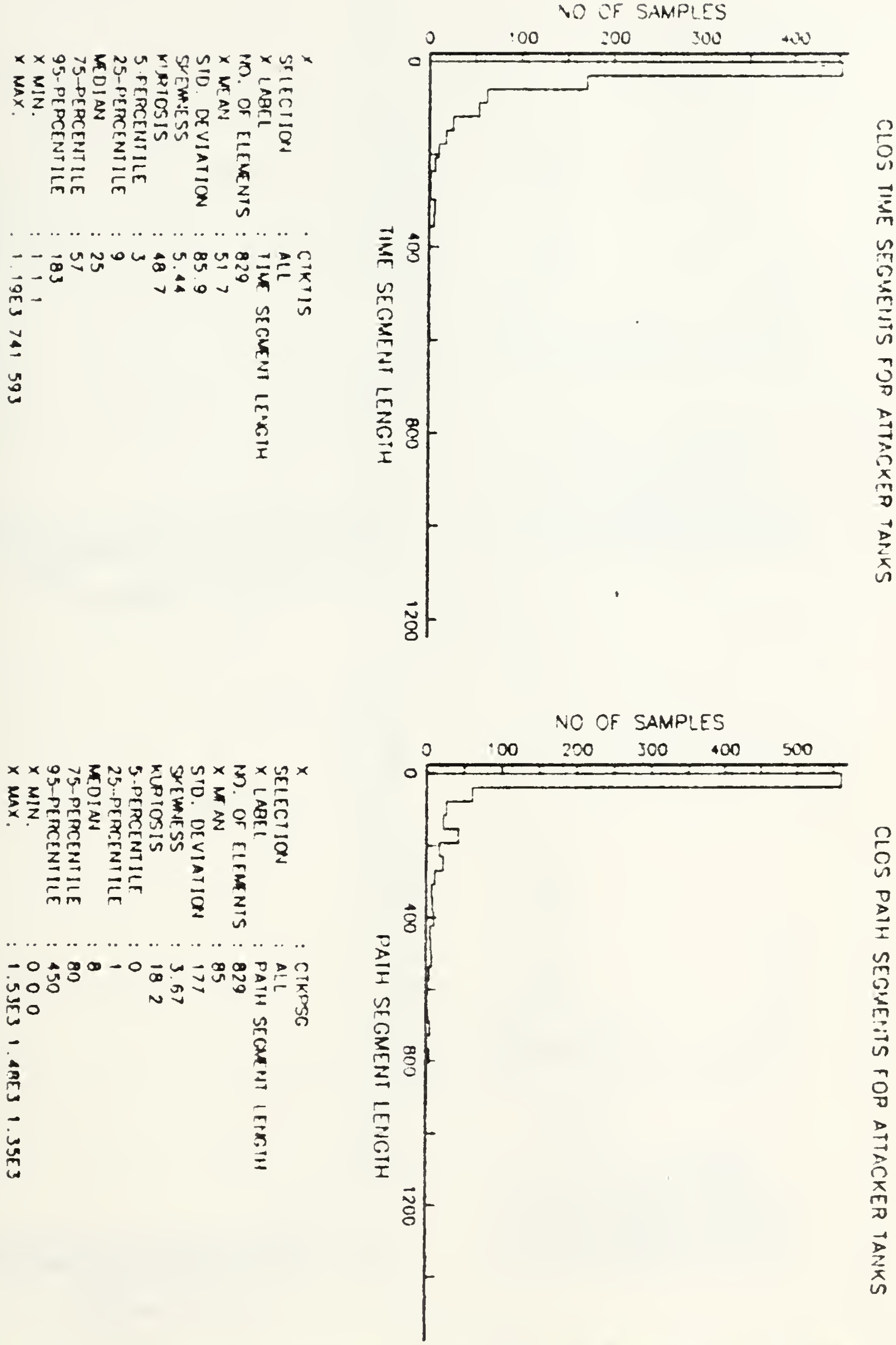
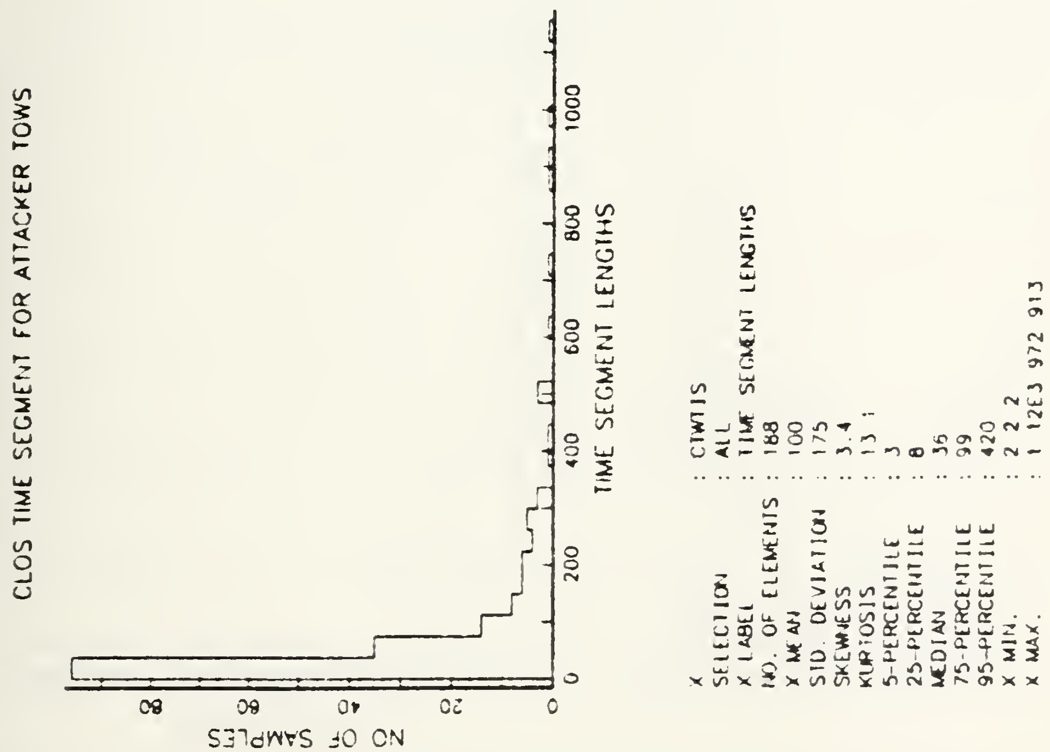


Figure C.1 Tank CIOS Time and Path Segment Histograms.



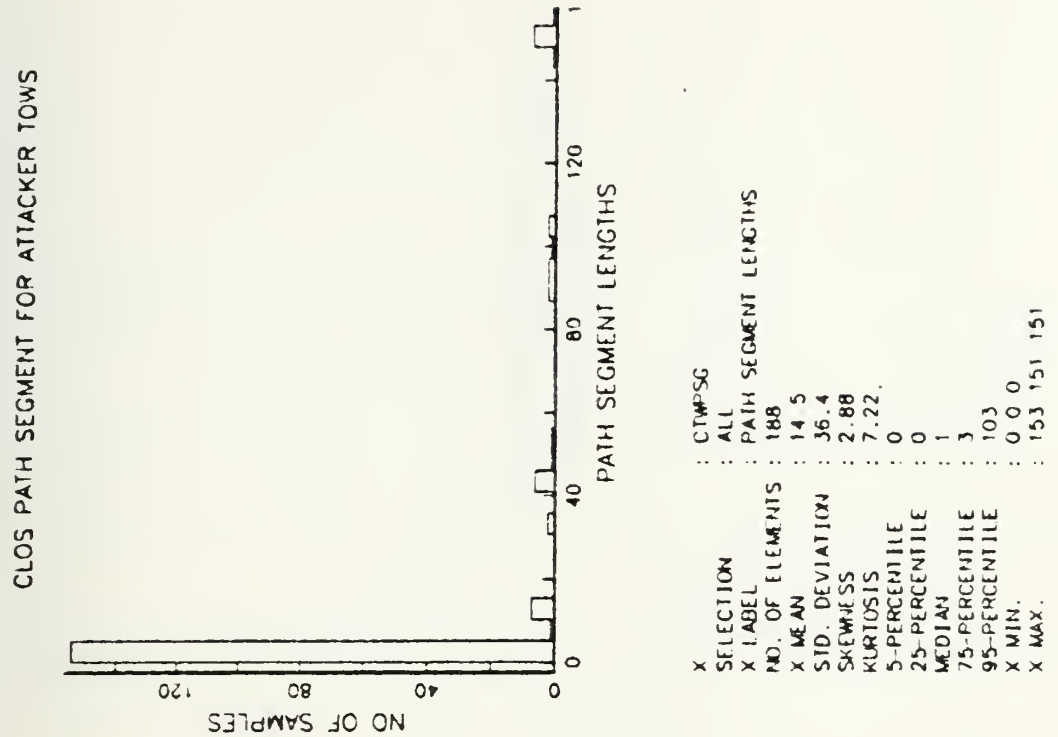
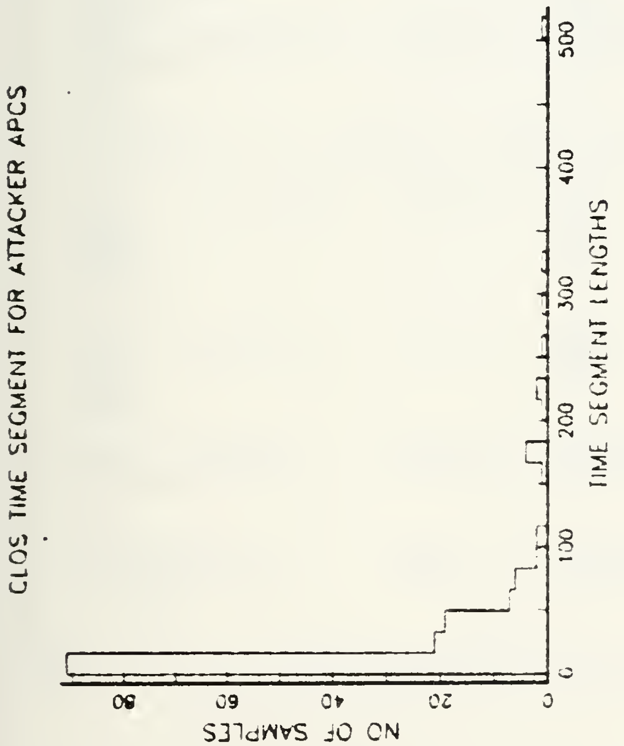
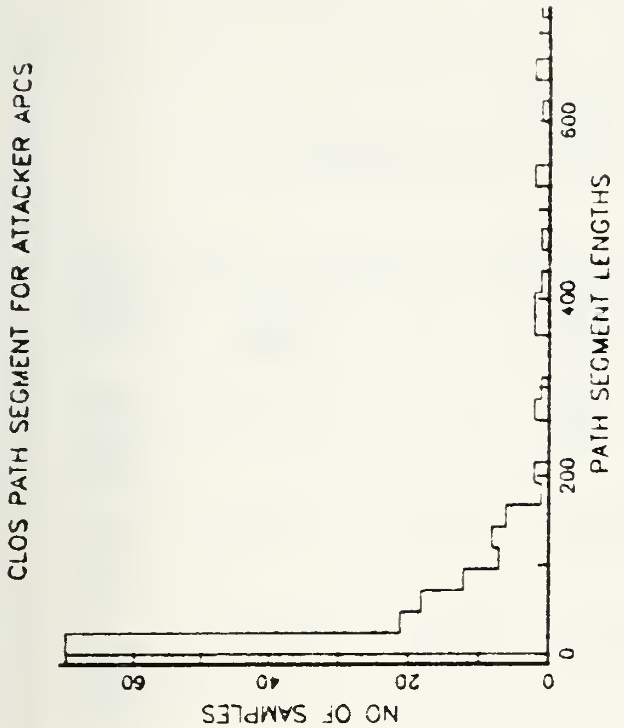


Figure C.2 Tow CLCS Time and Path Segment Histograms.



X	:	CAPTTS
SELECTION	:	ALL
X LABEL	:	TIME SEGMENT LENGTHS
NO. OF ELEMENTS	:	160
X MEAN	:	38.4
STD. DEVIATION	:	67.2
SKEWNESS	:	3.74
KURTOSIS	:	17.1
5-PERCENTILE	:	3
25-PERCENTILE	:	6
MEDIAN	:	15
75-PERCENTILE	:	36
95-PERCENTILE	:	177
X MIN	:	1 2 3
X MAX	:	503 328 299



X	:	CAPPSG
SELECTION	:	ALL
X LABEL	:	PATH SEGMENT LENGTHS
NO. OF ELEMENTS	:	160
X MEAN	:	85.1
STD. DEVIATION	:	139
SKEWNESS	:	2.74
KURTOSIS	:	7.47
5-PERCENTILE	:	0
25-PERCENTILE	:	7
MEDIAN	:	31
75-PERCENTILE	:	92
95-PERCENTILE	:	403
X MIN	:	0 0 0
X MAX	:	718 670 657

Figure C.3 APC CLOS Time and Path Segment Histograms.

TABLE XIV

RESULTS FOR TIME TO ENGAGE DATA

DATA FOR ATTACKER TO DEFENDER VEHICLES:

TYPE	DIST. FORM	λ	TEST TYPE	TEST STAT	D. F.	CRITICAL VALUE
Tank to Tank (87)	$1-e^{-\lambda(t-2)}$	.076	Chi Sq.	5.41	5	$\hat{\alpha} < .75$
Tank to Tow (15)	$1-e^{-\lambda t}$	.328	Lilfor.	.1497	NA	$\hat{\alpha} < .30$
Tank to Drag. (7)	$1-e^{-\lambda(t-3)}$	.2414	Lilfor.	.2857	NA	$.7 < \hat{\alpha} < .8$
Tow to Tank (23)	$1-e^{-\lambda(t-3)}$	.146	Chi Sq.	3.843	4	$.7 < \hat{\alpha} < .9$
Tow to Tow (8)	$1-e^{-\lambda(t-3)}$	.2857	Lilfor.	.25	NA	$.5 < \hat{\alpha} < .7$

DEFENDER TO ATTACKER VEHICLES.

TYPE	DIST. FORM	λ	TEST TYPE	TEST STAT	D. F.	CRITICAL VALUE
Tank to Tank (155)	$1-e^{-\lambda(t-1)}$	.1213	Chi Sq.	7.29	5	$.75 < \hat{\alpha} < .9$
Tow to Tank (30)	$1-e^{-\lambda(t-3)}$	.0719	Chi Sq.	3.415	4	$\hat{\alpha} < .75$
Tow to Tow (4)	$1-e^{-\lambda t}$	.0625	Lilfor.	.3544	NA	$\hat{\alpha} < .70$
Drag. to tow (10)	$1-e^{-\lambda t}$	.225	Lilfor.	.24	NA	$\hat{\alpha} = .60$

TABLE XV

RESULTS FOR TIME TO DETECT DATA

DATA FOR ATTACKER TO DEFENDER VEHICLES:

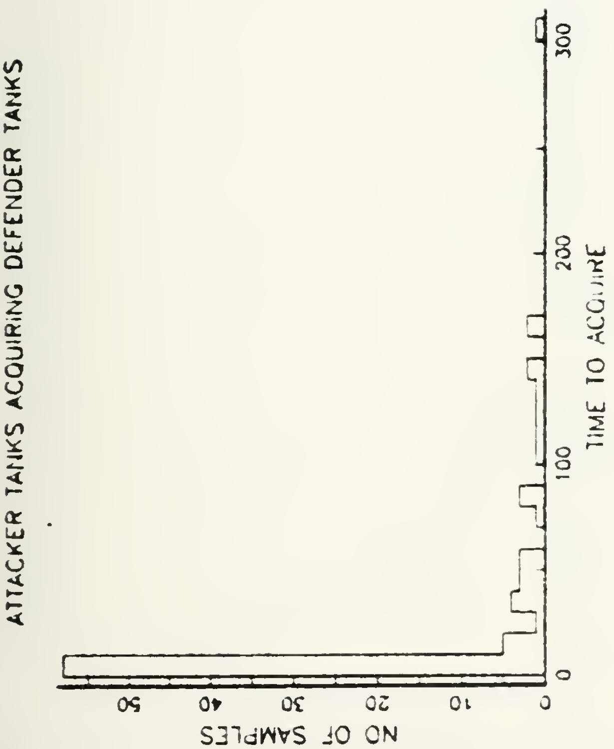
TYPE	DIST. FORM	λ	TEST TYPE	TEST STAT	D.F.	CRITICAL VALUE
Tank to Tank (87)	$1-e^{-\lambda(t-1)}$	.037	Chi Sq.	13.59	7	$.9<\hat{\alpha}<.95$
Tank to Tow (15)	$1-e^{-\lambda t}$	.0092	Lilfor.	.1642	NA	$\hat{\alpha}<.50$
Tow to Tank (23)	$1-e^{-\lambda(t-33)}$	.005	Chi Sq.	3.44	3	$\hat{\alpha}<.75$
Tow to Tow (8)		.0047	Lilfor.	.2458	NA	$\hat{\alpha}=.548$

DEFENDER TO ATTACKER VEHICLES.

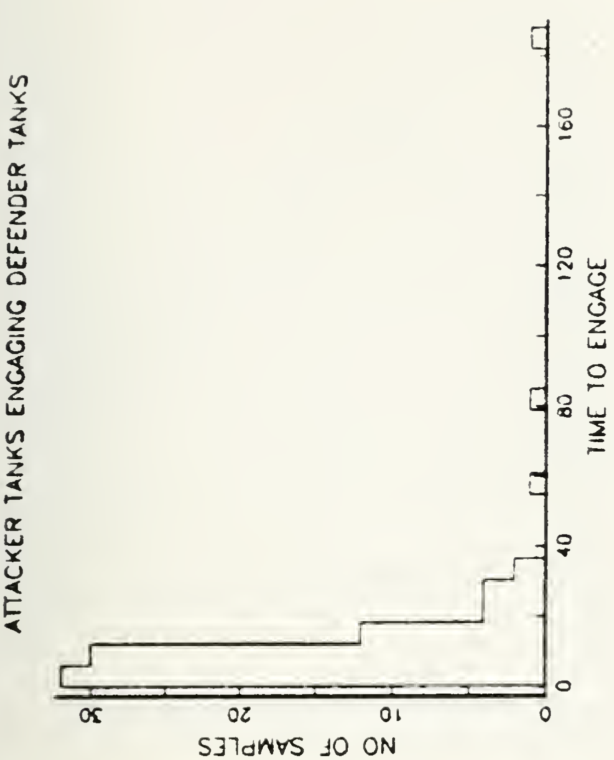
TYPE	DIST. FORM	λ	TEST TYPE	TEST STAT	D.F.	CRITICAL VALUE
Tank[1] to Tank (155)	$1-e^{-\lambda t}$	.0275	Chi Sq.	4.206	5	$\hat{\alpha}<.75$
Tow to Tank (30)	$1-.5e^{-\lambda t}$	.0196	Chi Sq.	1.385	4	$\hat{\alpha}<.8$
Tow to Tow (4)	$1-e^{-\lambda t}$	.0037	Lilfor.	.4147	NA	$\hat{\alpha}=.83.5$

---

[1] Two extreme data points were deleted from the data.



X	:	AQATDK[:2]
SELECTION	:	ALL
X LABEL	:	TIME TO ACQUIRE
NO. OF ELEMENTS	:	87
X MEAN	:	26.9
STD. DEVIATION	:	51.7
SKEWNESS	:	2.69
KURTOSIS	:	8.52
5-PERCENTILE	:	0
25-PERCENTILE	:	0
MEDIAN	:	0
75-PERCENTILE	:	34
95-PERCENTILE	:	146
X MIN.	:	0 0 0
X MAX	:	301 170 163



X	:	AQATDK[.6]
SELECTION	:	ALL
X LABEL	:	TIME TO ENGAGE
NO. OF ELEMENTS	:	87
X MEAN	:	12.9
STD. DEVIATION	:	21.8
SKEWNESS	:	5.82
KURTOSIS	:	40
5-PERCENTILE	:	0
25-PERCENTILE	:	5
MEDIAN	:	8
75-PERCENTILE	:	13
95-PERCENTILE	:	32
X MIN	:	0 0 0
X MAX.	:	162 83 55

Figure C.4 Attacker Tank to Defender Tank Acquisition Data.

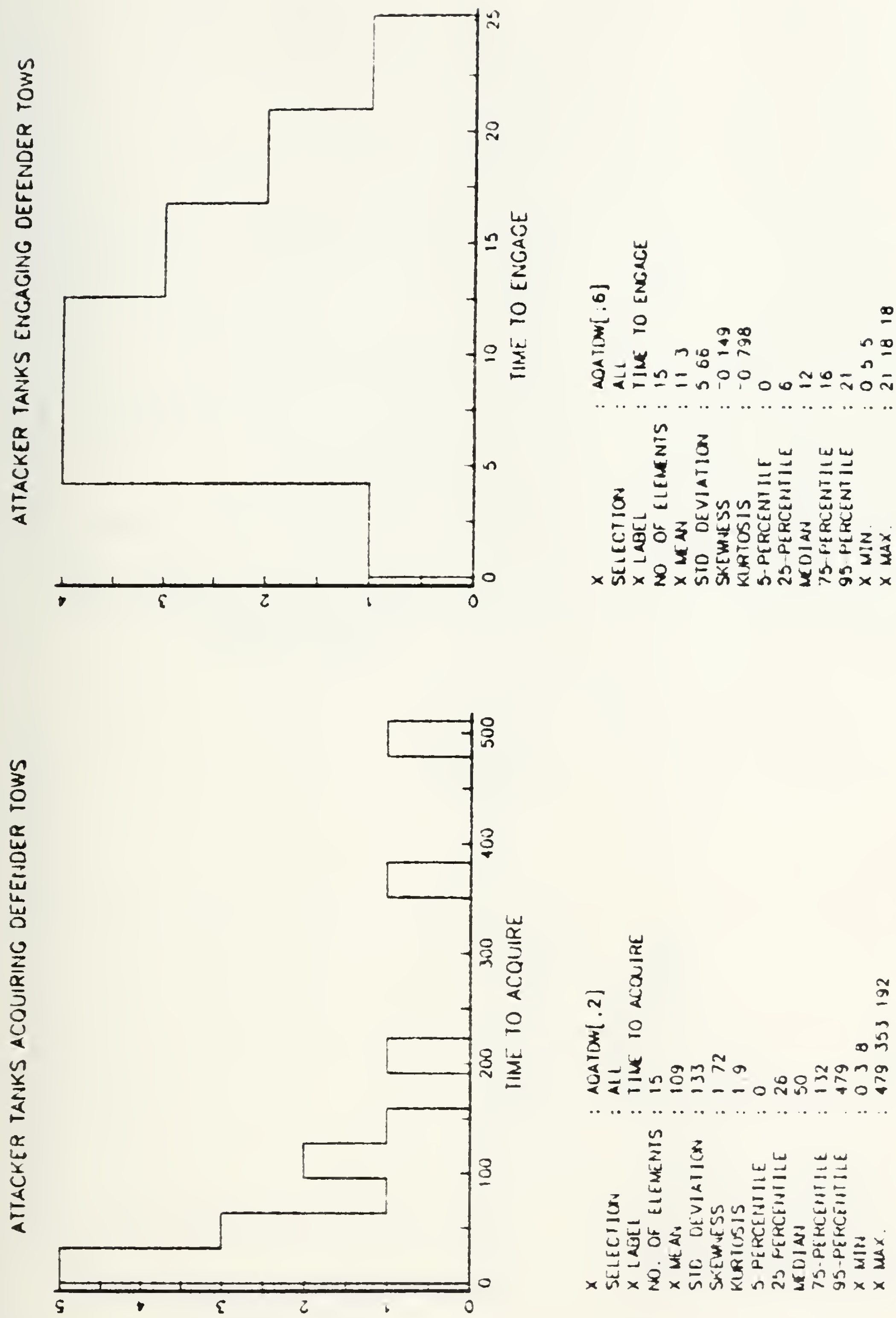
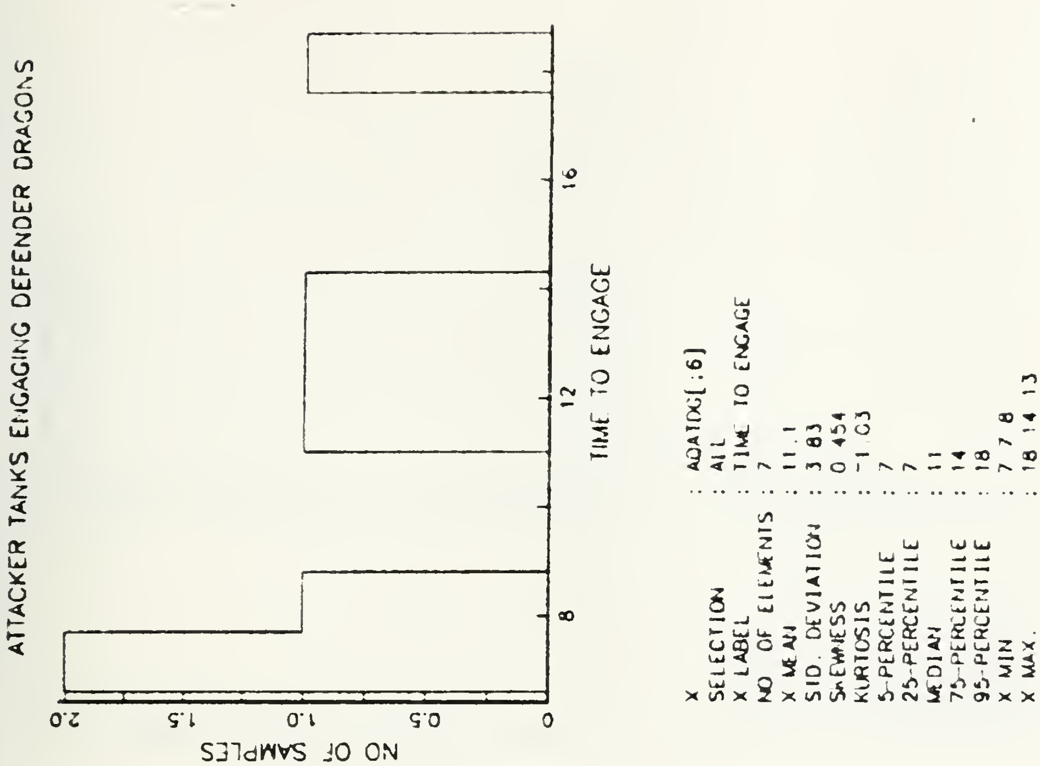


Figure C.5 Attacker Tank to Defender Tow Acquisition Data.



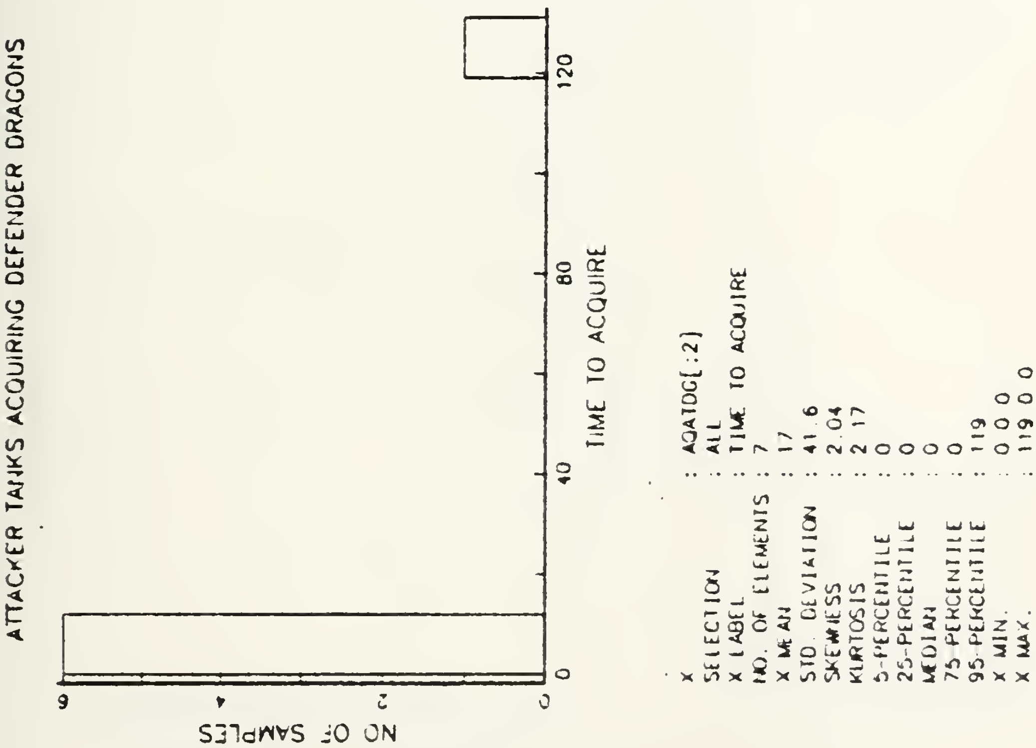


Figure C.6 Attacker Tank to Defender Dragon Acquisition Data.

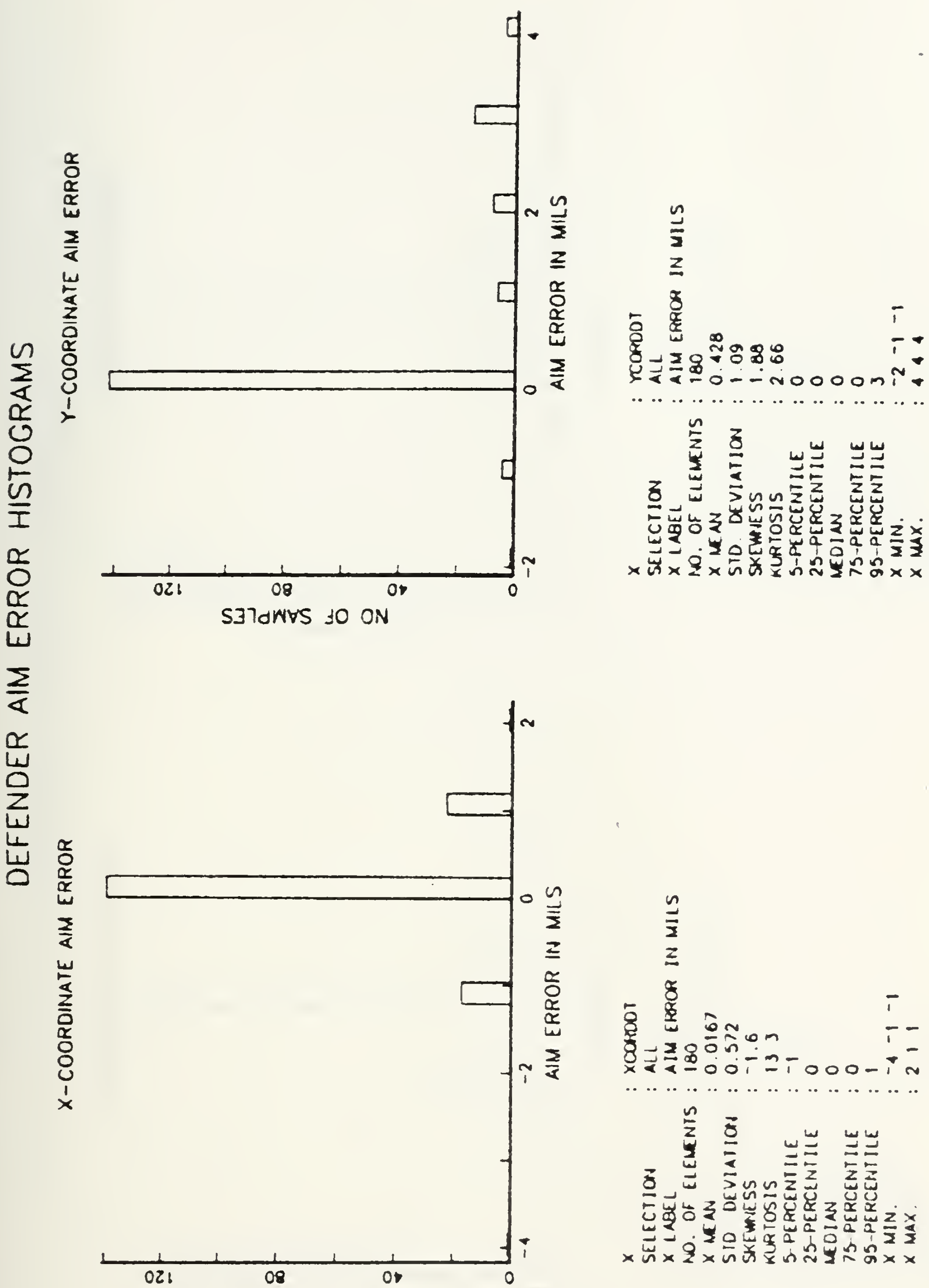


Figure C.7 Defender Aim Error Histograms.

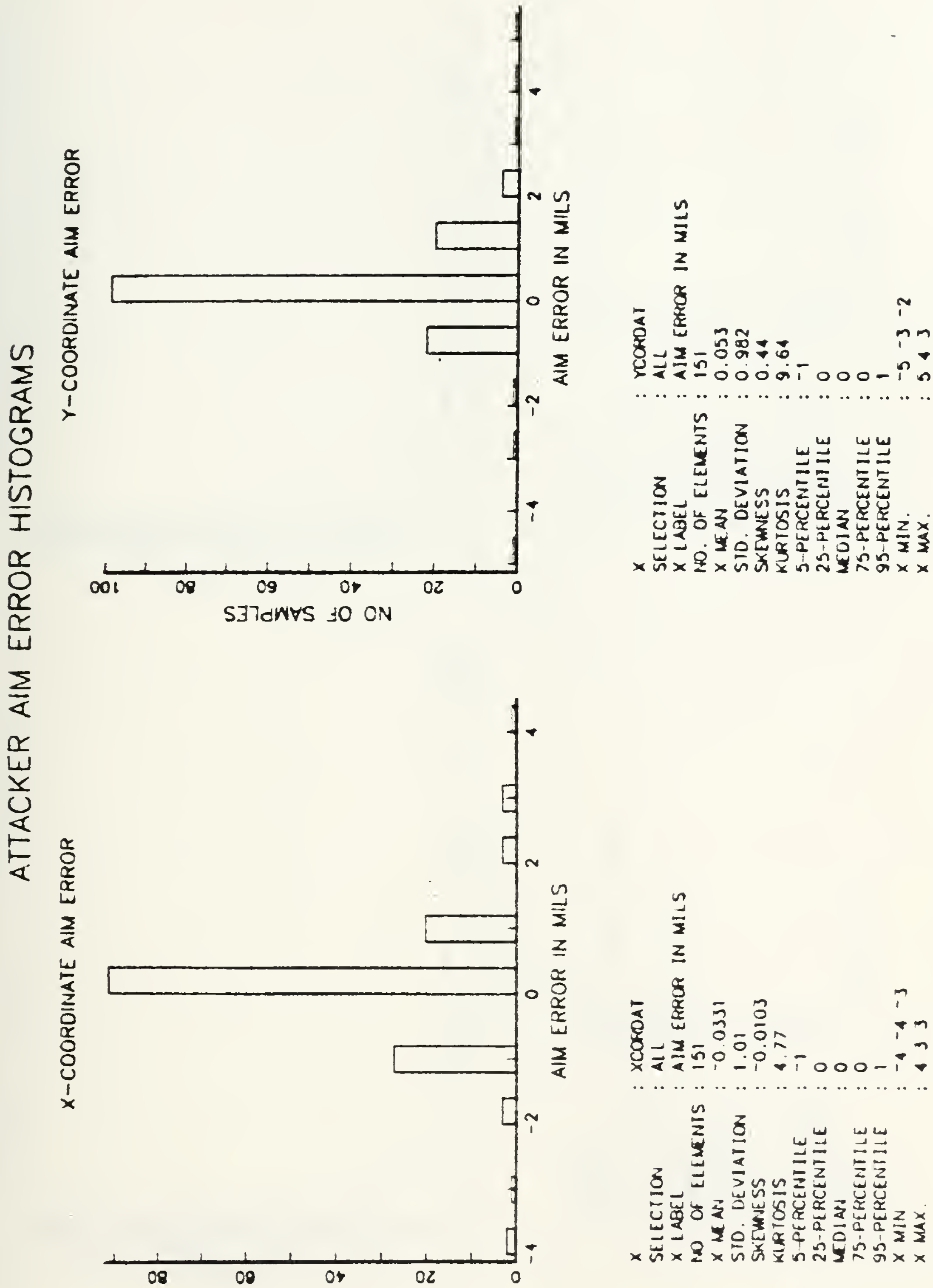


Figure C.8 Attacker Aim Error Histograms.

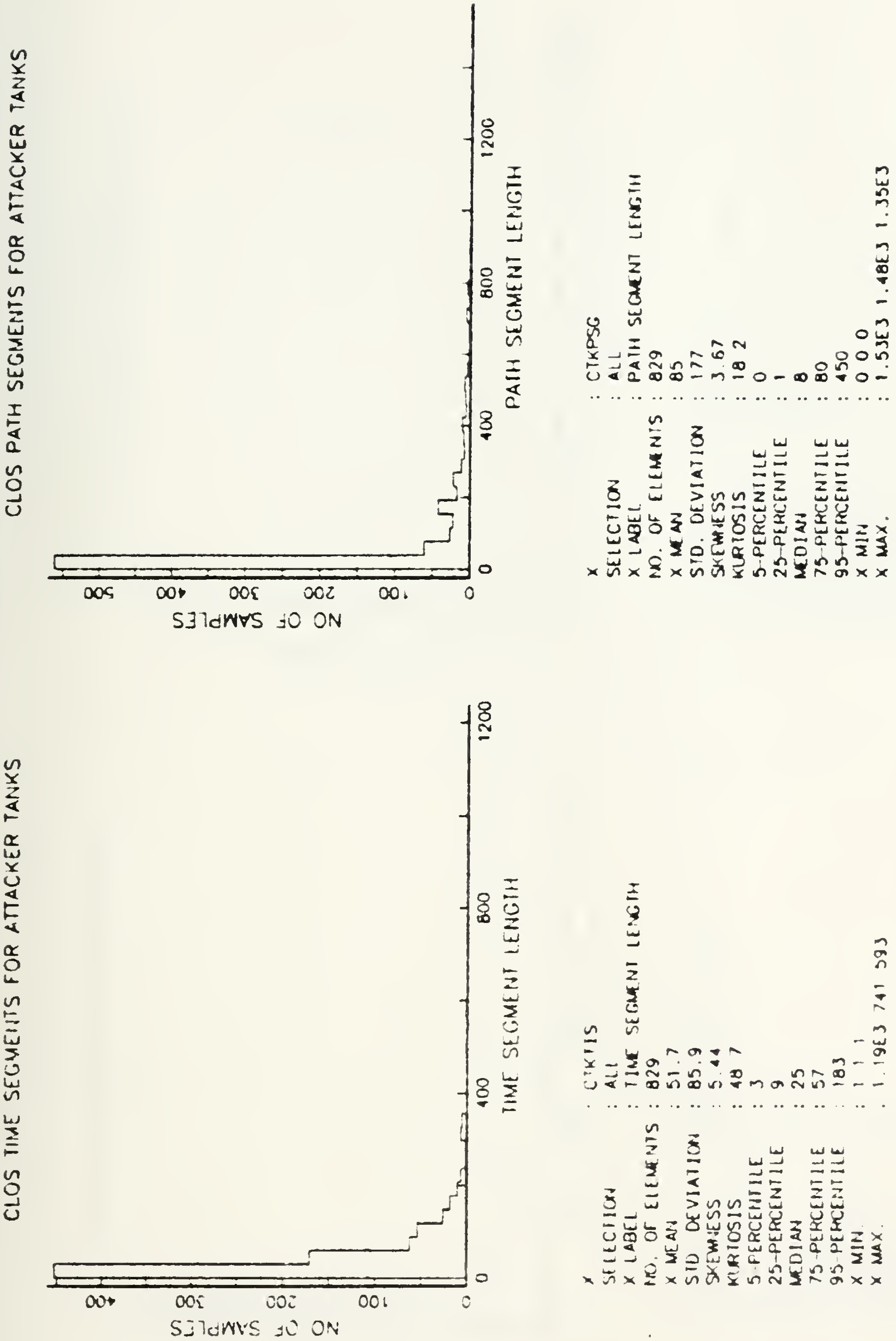


Figure C.9 Tank CLOS Segment Scatter Plots.

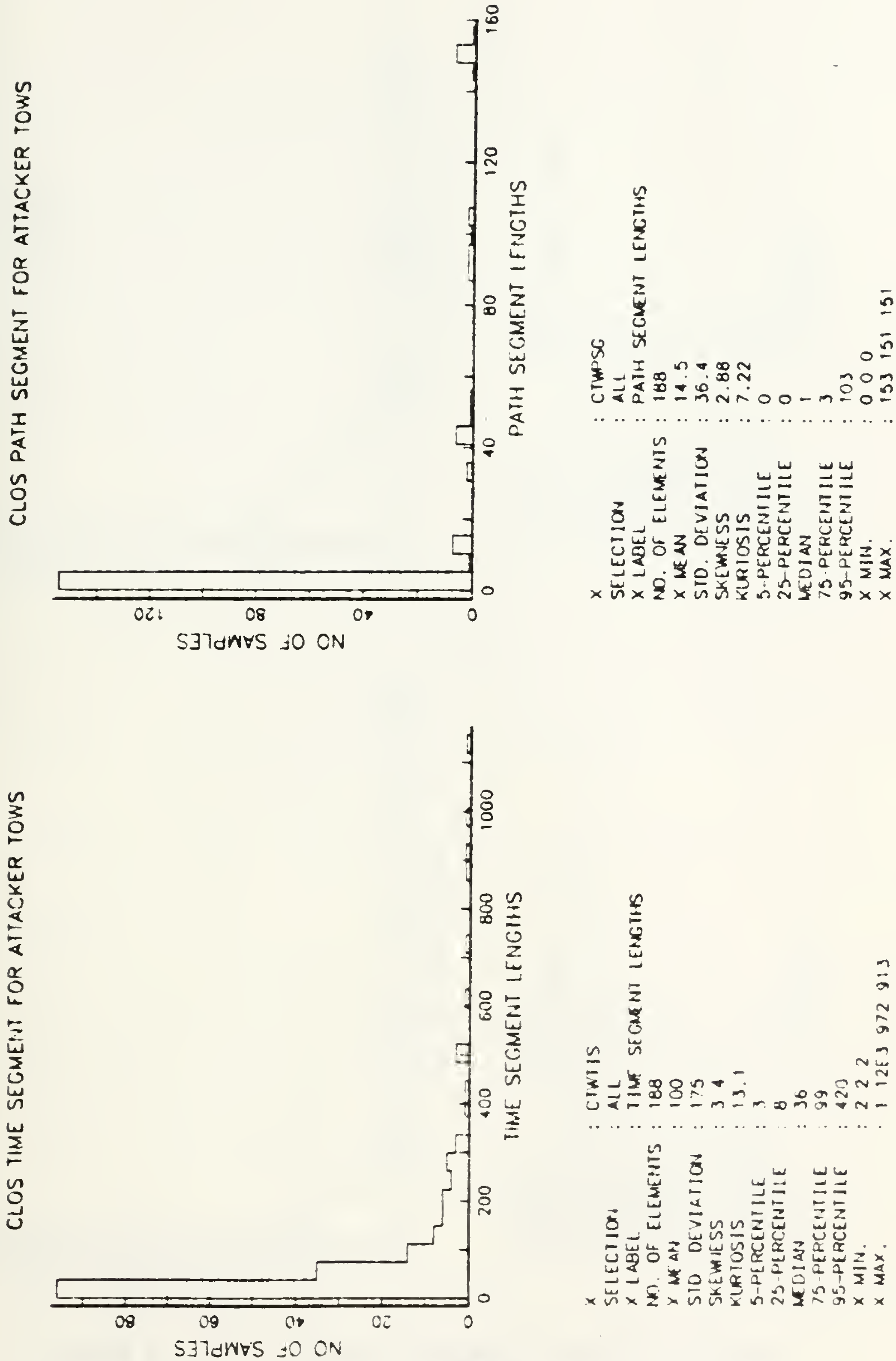
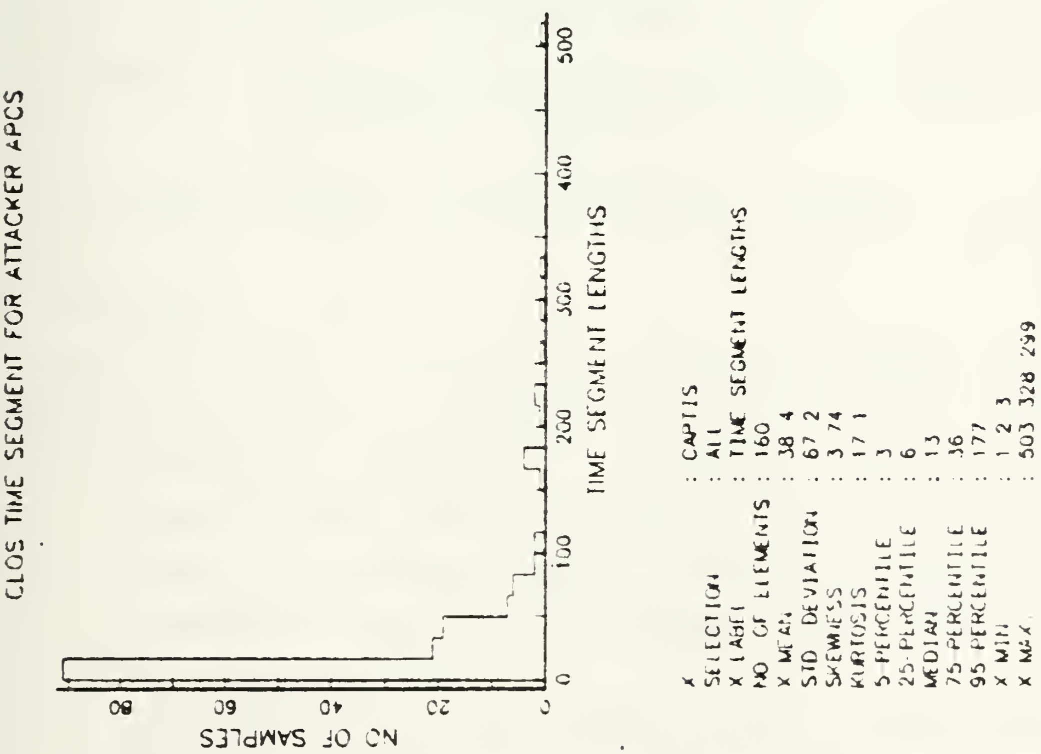


Figure C.10 Tow CLOS Segment Scatter Plots.



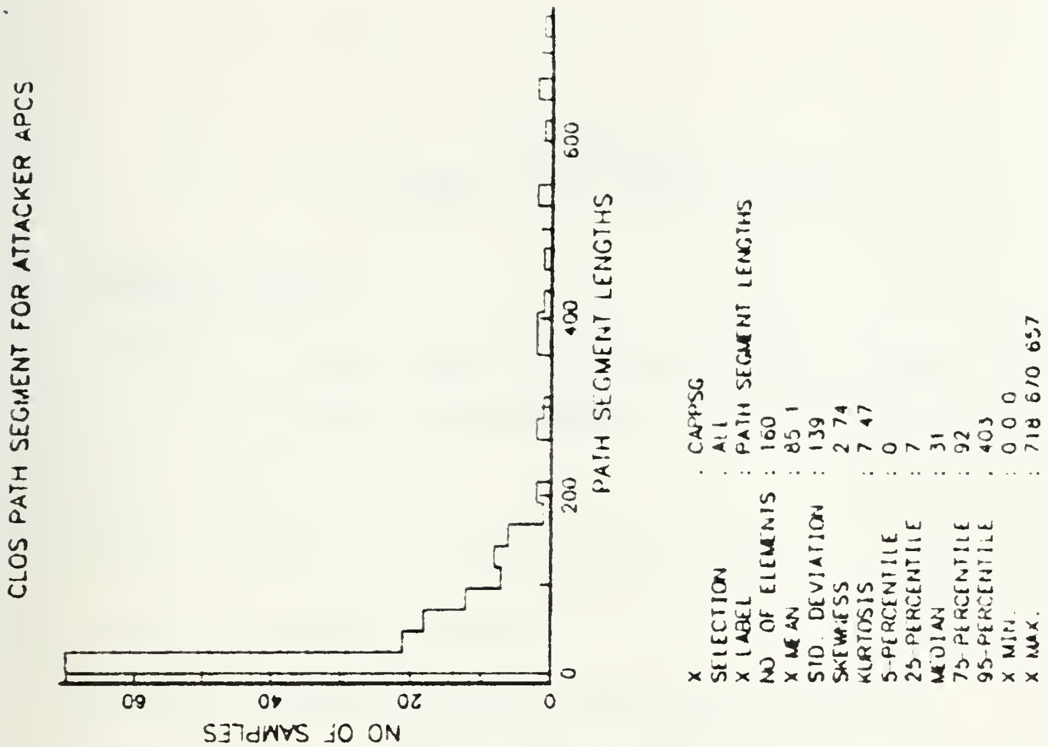


Figure C.11 APC CLOS Segment Scatter Plots.

APPENDIX D
GLOSSARY AND ABBREVIATIONS

A. ABBREVIATIONS

ARCCMS - Armor Ccbat Operaticns Model Support (field experiment)

AT - Anti-tank

CLCS - Conditional Line of Sight

CPFOR - Oppcsing Forces

TCATA - TRADOC Combined Arms Test Activity

TOW- Tube launched, optically tracked, wire guided missile system

TRADCC - (United States Army) Training and Doctrine Command

TRASANA - TRADOC Systems Analysis Activity

B. GLOSSARY

The fcllcwing definitions are extracted from gloasary that was obtained frcm TRASANA.

1. Alternate position - A vehicular firing position which covered the same target area a primary position. It was used when a primary position received intensive fire, or to confuse the enemy's target acquisition efforts.
2. Acquisition - The activity of discovering and lccating an actual target in sufficient detai to permit the effective employment of weapons.

3. Bound - That movement an individual vehicle or maneuver element made from one position to another. Ideally bounds were made from one covered and concealed position to another as rapidly as possible.
4. Conditional Line of Sight(CLOS) - CLOS existed when two sensor LOS conditions were met. First, LOS existed between a defending laser transmitter and an attacking vehicle DAS. Secondly, LOS existed between an offensive laser transmitter and a defensive vehicle's DAS. When those conditions were met both vehicles were assumed to have LOS with each other.
5. DAS- A laser energy receiving unit functioning on top of each attacking and defending vehicle, and on the searchlight mount of defending tanks.
6. Detection - When an observer was alerted to the presence of something of possible military interest that warrants further evaluation.
7. Engagement - The activity of laying on ;and firing at an actual target. An engagement can be one oor many firings at a single target.
8. False Target -Any target which was not of military value or not a live player of the opposing side.
9. Line of sight path segment - A portion of the path a moving target took over which LOS existed continuously to the sensor being considered. The path segment was a distance in meters over which an attacker traveled with LOS between an SLT and the DAS mounted on top of the vehicle.
10. Line of sight time segment - That length of time a target was on LOS path segment.
11. Overwatch element - The tactical role of an element positioned to observe the movement of another element and to support it with fires.

12. Time to acquire - The time for an observer to acquire a target based on line of sight. It started when LOS exists between an SLT (colocated with the observer) and the vehicle's DAS. It ended when an observer commands "target" or "gunner". (See time to engage)
13. Time to engage - The time for an engagement which began with the vehicle commander's command of "gunner" or the gunner's command "target", until the time of the first fiting at that specific target.

True target - Any tartet which was of military value and proper and correct for the weapon system to engage.

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